Three Essays on Open Innovation and Markets for Technology

by

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Contents

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Abstract

This thesis comprises three empirical studies examining topics in the field of innovation and technology management. These topics broadly concern firms' practices of open innovation and their engagement in markets for technology. The first two chapters of the dissertation (co-authored with Said Matr) focus on the outbound type of open innovation, in a setting, where the firm makes its knowledge (or part of it) for free to the outside parties, and investigate its implications for the focal firm and the industry, respectively. More specifically, in the first chapter, we propose two channels, through which a firm can potentially capitalize on a decision of adopting an outbound open approach in its intellectual property (IP) strategy for no direct financial benefits in return. The first channel involves selling subsequent intellectual assets for the focal firm in markets for technology to meet the demand resulting from the increased engagement of third parties in the liberated knowledge. The second one refers to bringing the subsequent external knowledge in-house via buying intellectual assets or building upon it internally. We capture the variation in IBM's IP strategy toward more openness, using the decision of IBM to pledge 500 of its patents to the public in 2005. The results from implementing a difference-in-differences approach between 1999 and 2010 provide support for the proposed mechanisms.

The second chapter investigates the knowledge-domain-level consequences of a firm-level decision to open up its IP strategy, in terms of the amount and type of the innovations subsequently created, market structure characteristics, as well as trading activities in markets for technology. The results from a difference-in-differences analysis of the impact of IBM's patent pledge of 2005 show that more patents and more radical patents are created, more entities (but not new-to-the-

field entities) file for patents, and more patent trades take place in the opened-up industries due to strategic openness. Our findings provide an empirical insight on the phenomenon of inside-out open innovation and improve our understanding with regard to its proclivity towards innovation advancement and innovation management at a broader level than the firm. Overall, among other contributions, these chapters establish a link between outbound openness and markets for technology at different levels of analysis.

Finally, the third chapter (co-authored with Eduardo Melero and Kurt Desender) addresses the question of what mechanisms may help mitigate firms' underutilization of external knowledge incorporation, and connects the literatures on markets for technology with the one on corporate governance to propose an answer. In particular, we focus on the widespread not-invented-here (NIH) syndrome, defined as a negative attitude toward outside knowledge that prevents organizations from absorbing external knowledge to generate further innovations, and argue that corporate-level actions can play an important role in neutralizing it. Accordingly, we examine the role of independent members of boards of directors, given their monitoring and advisory functions. We hypothesize and show that a higher presence of independent directors increases the probability of acquiring external knowledge in markets for technology, and that this relationship is particularly intense in settings where the NIH syndrome is more likely to be present. Furthermore, the effect is expected to be weaker when the CEO is in a strong position of power. Overall, our results confirm these hypotheses, suggesting that independent directors in corporate boards favor the incorporation of outside knowledge and help overcoming the NIH syndrome.

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Chapter 1

What’s there to Gain? Outbound Openness and Markets for Technology

1.1 INTRODUCTION

Over the past years, the practice of outbound open innovation[1] has become increasingly popular among big players in the software, semiconductors, pharmaceuticals, and automobile industries (West, Salter, Vanhaverbeke, & Chesbrough, 2014). Prominent examples are Johnson & Johnson's innovation lab in La Jolla, California, IBM's industry solution lab in Zurich Rüschlikon, or patent pledges of Red Hat (2002, 2017), IBM (2005), Google (2013), and many others. According to Linux Magazine, the 500 patents pledged by IBM "cost $10,000,000 to obtain (just in the U.S.) and are worth an unknown amount in licensing revenue"[2]. Interestingly, many such voluntary commitments to openness require no formal agreements to use the unlocked knowledge, meaning that outsiders can freely access it, without giving anything in return.

Firms' tendency toward making their knowledge or part of it available for free to outsiders (i.e. outbound open innovation[3]) in traditionally intellectual property (IP) intensive industries represents a "departure in strategy to say the least" (Fortune, 2016)[4]. Indeed, the conventional premise from the resource-based view strongly associates resource ownership with the ability of a firm to appropriate value (e.g. Barney, 1991; Collis & Montgomery, 1998). Thus, by granting free access to proprietary assets, thereby allowing for imitability, firms may risk losing competitive advantage over rivals (Dahlander & Gann, 2010). Then, why do corporate firms engage in

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[1] There are three main types of open innovation: outbound (inside-out knowledge flows), inbound (outside-in knowledge flows), and combined (both inside-out and outside-in knowledge flows) (Chesbrough, 2003; Chesbrough 2006a, 2006b). In this paper, we interchangeably use the terms outbound open innovation, outbound openness, and strategic openness to refer to the inside-out type of open innovation.
[2] **http://www.linux-mag.com/id/1975/**
[3] In this study, by outbound open innovation we refer to the non-pecuniary type of outbound open innovation, following the definition by Dahlander & Gann (2010, p. 704), "This [non-pecuniary outbound] type of openness refers to how internal resources are revealed to the external environment. In particular, this approach deals with how firms reveal internal resources without immediate financial rewards…" The second, pecuniary type of outbound open innovation, distinguished by the authors, refers to dealing with external commercialization of internal inventions and technologies via selling, licensing out or partnerships.
[4] **http://fortune.com/2016/07/22/the-radical-experiment-thats-changing-the-way-big-pharma-innovates/**

outbound openness, especially without direct financial gains in exchange? In this paper, we suggest two main mechanisms that the firm may use to capitalize on its practice of outbound openness. These channels primarily concern strategic openness' facilitating inward and outward knowledge flows, which in turn, induces the focal firm's engagement in markets for technology, in terms of transactions for IP rights. This may give rise to potential externalities for the opening up firm.

We complement to existing research that discusses possible incentives for firms to grant free access to their proprietary assets. These incentives comprise creating and obtaining returns from standards and their development (West, 2003; Henkel, 2006), advancing collective innovation (Levin et al., 1987), increasing the demand for their still proprietary assets that are complementary[5] to the opened-up ones and saving costs (e.g. Raymond, 1999; Alexy & Reitzig, 2013; Alexy, West, Klapper & Reitzig, 2018), or pursuing social goals (Raymond, 1999; Contreras, 2015). While these studies posit that other players in the market get more involved and contribute more to the opened-up intellectual assets (e.g. Parker & Van Alstyne, 2017), to the best of our knowledge, there is little research on whether and how the focal firms capitalize on and incorporate the newly created knowledge by others into their innovation processes. According to the literature on competitive dynamics, firms consider the possible reactions from other actors in the market, when making important strategic decisions. Therefore, arguably, following the practice of strategic openness, the way they manage their innovation processes will subsequently be altered due to the increased involvement and knowledge availability from third parties.

An important element in our theoretical arguments is that outbound openness reduces transaction and negotiation costs, as well as litigation threats (Wen, Ceccagnoli, & Forman, 2016). Due to the decrease in access costs and litigation risks, other firms get encouraged to become more

[5] These are often "razor and blade" (Tripsas & Gavetti, 2000) or "hardware and software" type of complementarities between the opened-up and still proprietary assets.

involved (Boudreau, 2010) and subsequently build more knowledge. Further, the focal firm can respond to the advances in innovation in different ways: by selectively buying innovations that other firms have developed via relying on the liberated knowledge, or by making further internal developments through combining its expertise with the new knowledge created by others in a specific technology. At the same time, because strategic openness indirectly enforces the outsiders' commitment to the liberated knowledge and technologies, as they create more complementary assets, thereby increasing their demand for the subsequent knowledge, the focal firm gets more opportunities for selectively selling its other internally developed knowledge.

Our study makes use of IBM's patent pledge of 2005 as a shock to the level of openness in the IP strategy of IBM (Wen et. al, 2016). Having the sample period from 1999 to 2010 allows us to implement a difference-in-differences approach to explore the consequences of the openness decision on the firm's engagement in markets for technology and the degree to and channels through which IBM utilizes the follow-on spillovers. Our results show that after 2005, IBM buys and sells more patents, proportionally to the level of openness in its IP strategy. However, we find stronger evidence for increased selling, rather than buying activities by IBM. We also find that IBM continues to create further knowledge developments, building upon external sources of subsequent knowledge more than on its own subsequent knowledge.

This study provides a new perspective on the firm's decision to waive its exclusivity rights and uncovers an indirect mechanism that firms may exploit for potentially profiting from opening up, especially in the presence of a well-developed market for technology. Naturally, this advantage should be weighed against the potential negative effects in terms of competition that may be imposed by the loss of property rights. In this sense, opening up may be a particular suitable alternative when (in countries/technological areas) there are well-developed markets for technology allowing the firm to trade on the subsequently created knowledge.

We contribute to the open innovation literature by providing a novel motivation and discussing potential indirect returns for the firms that adopt outbound openness pursuing no direct financial benefits. This link between open innovation and markets for technology has not been explored before, to the best of our knowledge. Put together, outbound open innovation could be viewed as complementary with trading in markets for technology. We also contribute to the literature on open innovation more broadly, by focusing on the effects of the outbound type of openness untangled from the inbound openness. While much of the prior research on open innovation has primarily focused on inbound open innovation, the outbound type of open innovation has received significantly less attention (Chesbrough, 2003). Importantly, however, our knowledge on the effects of inbound open innovation does not substitute that of outbound open innovation, and many studies have called for investigations on outbound open innovation effects (e.g. West et al., 2014). In this paper, we suggest that outbound openness is not necessarily something marginal in the firm's technology policy, but an important stepping stone for the subsequent development of innovation.

1.2 THEORY AND HYPOTHESES

1.2.1 Closed and Open Models of Innovation

Unlike in the traditional "closed" approach of innovation, where firms largely focus on in-house research and development (R&D), whilst constraining outsiders from using their technology (Cohen, Nelson, & Walsh, 2000), in "open" innovation models, firms tend to employ fewer boundaries on the use, development, and commercialization of the technology (Chesbrough, 2003). In this paper, we focus on a setting of purely outbound open innovation practices, where a firm explicitly grants the proprietary rights of its technology to the public domain (Katz & Shapiro, 1986; Boudreau, 2010). As patents or copyrights have long served as important mechanisms to protect firms from competitors by providing exclusive property rights for their innovations (Cohen et al., 2000; Hall & Ziedonis, 2001), without these rights, competitors, for instance, may be better placed in terms of their complementary assets or/and production facilities to utilize the opened-up knowledge by the focal firm (Dahlander & Gann, 2010). Therefore, one of the main challenges for firms practicing outbound open innovation is the risk of not being able to appropriate benefits from their decision (Helfat & Quinn, 2006). Nonetheless, firms are increasingly adopting openness in their innovation approaches, and therefore, we briefly discuss the prior literature on the motives for adopting strategic openness in the next subsection.

1.2.2 Motives for Adopting Outbound Open Innovation

We mentioned in the introduction some of the studies that extend the understanding of the underlying reasons why firms choose to open up their knowledge (e.g. von Hippel, 1998, 2005; von Hippel & von Krogh, 2003; West, 2003; Henkel, 2006; Alexy & Reitzig, 2013; Alexy et al., 2018). The theoretical premise from the previous literature is that opening up is not always detrimental for appropriating benefits from an innovation (von Hippel, 1998, 2005; Henkel, 2006; von Hippel & von Krogh, 2003). Several works link openness with appropriation benefits in return from resource complementarities. For instance, primarily addressing the question of who opens up their knowledge, Alexy & Reitzig (2013) suggest that by doing so, firms can enhance the demand for their complementary resources controlled by the firm. In the context of open source software (OSS), Fosfuri, Giarratana, & Luzzi (2008) find that the possession of complementary assets increases the likelihood of introducing OSS products. The authors argue that the control over complementary resources helps the firm to appropriate value from OSS development (Arora, 1995), and gives the firm a bargaining power to reduce potential litigation risks from other entities against OSS products (Ziedonis, 2004). Building on the resource-based view, Alexy et al. (2018) provide contexts when openness can help/harm firms, their competitors or both. In particular, the paper argues that when the cost of production is high for an innovation and it is strongly positioned with complementary assets, the firm may decide to open it up and utilize those complementary assets to internalize the benefits from the opened-up knowledge.

Other explanations for engaging in openness include the following. A study by Henkel, Schöberl, & Alexy (2014) suggests that firms' deliberate waiving of some of their IP rights can be explained by the consumer demand pull for openness and that such behavior brings in a positive feedback loop, eventually making openness become another dimension of competition. Alexy, George, & Salter (2013) propose that firms may also engage in strategic openness to increase collaborative activities with others in the market. The authors argue that firms will be more prone to openness, especially when there is a high partner uncertainty, high coordination costs, and when potential known partners are unwilling to collaborate. Other reasons for which firms may decide to grant access to their proprietary knowledge include endorsing product interoperability via standards creation or pursuing social goals (Contreras, 2015).

Though a common assumption in these studies is that outbound openness induces third parties' involvement in the opened-up technologies, to the best of our knowledge, there is still little research that has focused on whether and how the firms that decide to open up, can internalize the involvement from other entities in their further innovation processes. Focusing on the effect on outsiders, Wen et al. (2016) analyze how strategic openness affects new product introductions by start-up firms. The authors find that on average, more new product introductions occur by startups in areas of knowledge with higher rather than lower degrees of openness. Murray et al. (2016) find a positive impact of the level of openness associated with unlocked research tools on the subsequent innovations' amount and type in a context of academic researchers. However, neither of these papers consider the consequences for the opening firm (IBM and Dupont, respectively) on its innovation strategy, which is key in this paper.

One primary focus of this study is on how the level of openness in the IP strategy of a firm affects the opening firm's participation in markets for technology. Hence, we further link the adoption of strategic openness to being on the supply and demand sides of markets for technology, following Arora & Gambardella (2010).

1.2.3 Outbound Openness and Markets for Technology

While developing new products and technologies is essential for survival and growth in today's business environment (Swink, 2003), the possibility of purchasing technological assets can also provide firms with strategic flexibility to utilize on market opportunities (Cesaroni, 2004). Markets for technology, where inventors (organizations, individual inventors, etc.) trade knowledge assets, have grown substantially over the past decades (Arora, Fosfuri, & Gambardella, 2001; Chesbrough, 2003; Arora & Gambardella, 2010) and have received considerable attention from business and economics scholars, despite the general assumption of being underutilized. Prior literature provides mixed evidence on the relationship between markets for technology and IP protection (Arora & Gambardella, 2010). Some studies find a positive association (e.g. Arora, 1995; Anand & Khanna, 2000; Gans, Hsu, & Stern, 2002), while other works find that weak or ineffective patent regimes are likely to increase trades in technology markets, or else, that IP protection has no effect on these markets (e.g. Veugelers & Cassiman, 1999; Smith, 2001; Nagaoka, 2002; Fosfuri, 2004). Our paper adds to this stream of research by investigating the link between outbound openness (i.e. explicitly giving up IP protection for some pieces of knowledge) and markets for technology. In the next section, we hypothesize on possible mechanisms through which the focal firm can capitalize on its practice of outbound openness, and Figure (1) depicts the hypotheses that we discuss in the following subsections.

Insert Figure 1 about here.

1.2.4 Internalization Mechanisms of Outbound Openness

Selling in markets for technology. As a firm waives the proprietary rights to its technology, other players in the market are per se exposed to more "usable" knowledge[6]. Exposure to external knowledge sources increases the likelihood that other firms will seek to make use of the external knowledge (Huber, 1991), especially if the contribution is significantly large. This can be explained by the fact that the voluntarily liberated knowledge translates into decreased transaction and negotiation costs and litigation threats (Boudreau, 2010; Wen et al., 2016) for others, which encourages them to incorporate the opened-up knowledge into their internal innovation processes. If before, third parties had to pay royalty fees or else, buy the proprietary rights to incorporate it without infringing, now these entities can freely access and make use of this knowledge.

To be able to exploit the liberated knowledge, outside actors are likely to create other supporting assets. These supporting assets can take the form of complementary downstream resources, as such resources related to manufacturing, marketing, or distributing the products that use the opened-up knowledge. This, in turn, will tend to increase third parties' valuations of future

[6] As patents are public, anyone can access the information provided in the patent. In this context, by "usable" knowledge, we mean that for the opened-up patent, the inventor is given the right to use the relevant knowledge without the need to pay any royalty fees. Additionally, the inventor is exempt from a litigation threat for using the knowledge in the patent. Therefore, the usability of the knowledge is per se increased with strategic openness.

inventions and further advancements of the opened-up knowledge. Consequently, the demand for the subsequent innovations based on the specific pieces of knowledge will tend to increase. In other words, as outsiders incorporate the opened-up knowledge into their internal innovation processes, by investing in complementary assets to support the knowledge usage and commercialization, they will tend to have a higher demand for related inventions. Hence, the focal firm practicing strategic openness, will obtain more opportunities for selling its other proprietary knowledge to outsiders[7].

Two main factors can help explain that the focal firm could indeed translate these increased selling opportunities into supplying the demanded pieces of knowledge following its practice of outbound openness. First, due to its prior experience with the opened-up knowledge, one could argue that the firm is naturally equipped with a stock of relevant knowledge, which would make it possible for the firm to satisfy the increased demand. Second, for the increased demand to be actually satisfied by the focal firm, the gains from selling opportunities would arguably need to exceed the costs from losing ownership and control over its other proprietary assets. As the probability of engaging in beneficial selling transactions would plausibly increase with higher demand and involvement from outside parties, in the hypothesis below, we expect the focal firm to sell more of its still-proprietary knowledge after the decision to open up.

Hypothesis 1. The more openness the firm adopts in its IP strategy, the more knowledge it sells in the markets for technology.

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[7] Though outside the scope of the current study, the increase in the demand for relevant inventions will not necessarily only benefit the focal firm. Since outbound openness can also induce other firms to create their own advancements of knowledge (see further development of the hypotheses; and for a more detailed discussion, see Ayvazyan & Matr, 2019), the increased demand for the subsequent knowledge can be satisfied by external parties as well.

Using the subsequently created knowledge via buying in markets for technology. Another logical reaction from outside parties to the reduction in the costs and risks of incorporating the liberated knowledge is to engage in creating subsequent developments[8], for instance, by building upon it or/and by recombining it with their pre-existing stocks of knowledge. In the context of platform development, Parker & Van Alstyne (2017) argue that platform openness stimulates third-party developers to build upon the made-free knowledge and generate R&D spillovers. As others having diverse capabilities innovate and contribute to these opened-up technologies, the possibilities of knowledge recombination and new knowledge creation increase. Galasso & Schankerman (2015) document an increase in the follow-on inventive activities in the aftermath of *involuntary* waivers of exclusivity rights, i.e. patent invalidation decisions from the court. Despite the decision of patent invalidation, follow-on innovators are still required to recognize prior art, though now, without the need for paying any royalty fees (i.e. reduced costs for using the knowledge). Similarly, in the context of *voluntary* waivers of exclusivity rights (i.e. outbound openness), third-party engagement in advancing the liberated knowledge will tend to increase.

The increased involvement from outside parties in developing new knowledge will be reinforced by the increased demand for the subsequent knowledge from those engaging in creating complementary assets, as a response to strategic openness (as hypothesized previously). From the focal firm's point of view, the advancements of the liberated knowledge by others will, in turn, represent opportunities for internalizing these spillovers through two main channels. First, the focal firm could selectively buy from the new knowledge. Second, it could incorporate the further developments by building upon them within the limits of non-infringement of property rights.

[8] Building complementary assets and engaging in creating further knowledge are not necessarily mutually exclusive. Third parties may do both and this could depend on various factors (e.g. the degree of their upstream and downstream capabilities).

These two mechanisms (at least partially) can be explained through the lens of the concept of absorptive capacity (Cohen & Levinthal, 1989, 1990). Having the privilege of familiarity and a likely considerable experience with the previously proprietary knowledge, the focal firm will possess important absorptive capacities for identifying and evaluating the follow-on inventions (Arora & Gambardella, 1994). These abilities will facilitate the firm's engagement in buying transactions of the subsequent external pieces of knowledge, which can potentially be more value-enhancing in terms of their suitability with the firm's innovative needs. In addition, being familiar and experienced in the liberated knowledge, focal firms would likely be equipped with the necessary complementary assets to be able to incorporate the outside knowledge into their internal innovation processes. These two factors, namely absorptive capacities and complementarities between internal and external knowledge are, in fact, two of the three main drivers of the demand side of markets for technology, as identified by Arora & Gambardella (2010). The third driver relates to the so-called "Not-Invented-Here" (NIH) syndrome, which largely refers to the irrational bias against outside sources of knowledge/technology. This syndrome may, at the extreme case, lead to an exclusively internal recombination of knowledge, thereby potentially putting the firm into a competency trap (Levitt & March, 1988; Levinthal & March, 1993). However, it is less likely to be dominant in firms that adopt open innovation approaches, since these firms are supposedly more "open-minded" towards outside-in or inside-out knowledge flows[9]. Thus, while absorptive capacities will tend to help the focal firm to identify and evaluate knowledge developments from third parties for buying decisions, the complementarities between internal knowledge and external knowledge advancements, together with a low propensity that the firm

[9] See Cassiman and Valentini (2016) for a discussion on the complementarities between outbound and inbound open innovation and, in particular, on the role of reductions in cognitive, organizational and transaction costs.

suffers from the NIH syndrome, will tend to mitigate the generally assumed underutilization of knowledge acquisitions in markets for technology.

Taken together, the above-mentioned arguments support the premise that with strategic openness, the focal firm will get more opportunities for engaging in buying transactions in markets for technology. Hence, we hypothesize:

Hypothesis 2. The more openness the firm adopts in its IP strategy, the more knowledge it buys in the markets for technology.

Using the subsequently created knowledge via building upon it. The second channel through which the firm may internalize the knowledge spillovers from the opened-up knowledge is via building upon these external knowledge advancements. This is especially relevant for situations, where directly incorporating others' follow-on knowledge with the help of the firm's complementary assets via buying in markets for technology (see the discussion above) is likely not an optimal choice for the firm. For instance, with the increased availability of subsequent knowledge due to outbound openness, it is possible that some of this externally developed knowledge is simply not yet commercializable and further technical developments are still required to ultimately take the knowledge to market. Considering that the focal firm can use its absorptive capacities of identifying and evaluating external pieces of knowledge from the pool of sequential inventions (due to its existing experience and know-how with the liberated knowledge), with increased available knowledge, the firm will be provided with new possibilities for further recombining and advancing the technology without infringing on others'[10].

[10] Importantly, the newly created knowledge by the focal firm should be sufficiently differentiated from and not infringing on others' inventions. Otherwise, the risks and costs of infringement could cancel out the potential benefits from building upon the external follow-on developments of the liberated knowledge.

Prior research has argued that building upon the subsequent technical developments for generating new knowledge is, in fact, beneficial for the focal inventing firm, as it may allow for capitalizing on the firm's previous inventive efforts (Belenzon, 2012). The intuition behind is that by "reabsorbing" the subsequent knowledge, the firm may mitigate the potential negative effects of (involuntary) knowledge spillovers[11] and sustain its long-run earnings. Then one could argue that building on the follow-on knowledge would be especially important, when practicing outbound openness, where the firm itself allows for knowledge spillovers. This is the case, since with more involvement from others in creating developments of the opened-up knowledge, the competitive environment becomes more dynamic, increasing the need for the focal firm for developing and renewing prevailing capabilities to match the changing requirements of the environment (Teece, Pisano, & Shuen, 1997). The increased "competition" anticipated by the firm's adoption of outbound openness implies that the firm should protect its market position and continuously develop new knowledge to be able to compete in these fields. Thus, as illustrated in Figure 2, we argue that the increased subsequent inventive output due to outbound openness would lead to more opportunities for the firm for internalizing those externalities. Hence, our third hypothesis:

Hypothesis 3. The more openness the firm adopts in its IP strategy, the more knowledge it builds upon the subsequently created knowledge.

1.3 RESEARCH SETTING

Studies on knowledge transfer among firms and on innovation have relied on the outcomes of technology licensing transactions (e.g. Arora & Ceccagnoli, 2006; Fosfuri, 2006; Nagaoka &

[11] For a discussion on the negative effects of knowledge spillovers, see e.g. Spence (1984), Aghion & Howitt (1992).

Kwon, 2006; Gambardella, Giuri, & Luzzi, 2007) or collaborations (e.g. Singh, 2005; Schilling & Phelps, 2007; Jugend et al., 2018). We argue that these proxies do not allow disentangling the effect of outbound open innovation for the following reasons. Firms engaging in licensing or collaborations remain in control, at least partially, of the flow of knowledge in terms of who can use the knowledge or how often they can use it. Specifically, in case of licensing, the firm chooses to whom to license, while getting royalties in return. On the one hand, this naturally limits the number of users, who can benefit from the knowledge, and on the other hand, the firm still holds the ownership of the knowledge. Similarly, in case of a collaboration, the firms remain the owners of the knowledge, and the knowledge flows in both directions, as the collaborating firms make their knowledge available to each other. As a result, the effect of outbound and inbound openness appears combined and separately undistinguishable.

We deviate from these studies, by testing our hypotheses in a different setting, namely patent pledges. Specifically, our research context is IBM's IP strategy and its consequences for innovation-related outcomes for IBM itself during the period from 1999 to 2010. In 2005, IBM announced that it had decided to donate 500 of its patents to the public in support of the development of the OSS community. Being royalty-free, IBM's patent pledge did not require any formal agreement for anybody to use the patents in the pledge. This means that anybody could use the opened-up knowledge without, for instance, a requirement of giving up their own IP rights. These properties make the setting of IBM's pledge a pure form of outbound openness. In addition, IBM made the decision of pledging these patents considering their substantial economic importance, as well as their ample coverage of technological classes. According to Linux Magazine, the 500 patents "cost $10,000,000 to obtain (just in the U.S.) and are worth an unknown amount in licensing revenue"[12]. IBM's patent pledge announcement (2005) claimed that that patent pledge was by far the biggest contribution to the OSS, in terms of the number of patents. The announcement (2005) also stated that "Fostering Innovation, Interoperability and Open Standards" were the goal of the pledge.

Nevertheless, several alternative motives behind IBM's pledge have been discussed in various academic and non-academic sources. For instance, IBM pledge was suspected to be motivated by the dispute between IBM and Santa Cruz Operation (SCO) Group in 2003, where IBM was accused of infringing SCO's UNIX code (Goettsch, 2003). After its counterclaim against SCO in 2004, IBM decided to offer the 500 patents in the pledge for free, arguably, to provide the OSS community with insurance about Linux, the open-source operating system IBM supported. Meanwhile, Alexy & Reitzig (2013) note that the patent pledge could have been reasoned to stimulate the demand for IBM's complementary assets and the sales of its hardware products. Another speculation regarding this pledge refers to the debate about European software patent laws. Some observers doubted that IBM's move was aimed at signaling to the European legislators that software patents did not necessarily hinder the innovation process. Altogether, we argue that these speculations do not seem to be directly related to IBM's strategy in markets for technology. Thus, IBM pledge appears to be a suitable context to address our research question.

1.3.1 Identification Strategy

Empirically, we perform difference-in-differences analyses incorporating IBM's pledge of 2005 at two different levels. The first set of analyses includes the level of knowledge domain, represented by technological classes, according to The United States Patent Classification (USPC).

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[12] **http://www.linux-mag.com/id/1975/**

We use these class-level analyses (with class-year type of observations) to explain the temporal variation outcomes of patent trading (i.e. selling and buying) activities (for hypotheses 1 and 2), using a score of openness for each technological class. To understand the construction of this score (see "Independent Variables" subsection), we next explain our identification strategy at this level. First, we identify the treated group of technological classes, if the class includes any of the 500 patents that IBM pledged in 2005. There are 50 such technological classes. The classes without any pledged patent, to which IBM had significantly contributed up until 2005 – that is IBM patents counted for more than 2.5% of all the patents in the class or IBM had more than 200 patents in the class[13] - serve as the control group of technological classes. There are 127 control classes, leaving us with 177 classes in total. Assigning an openness score to each of these technological classes allows us to explore whether IBM tends to buy or sell more patents in areas of knowledge in related to their levels of openness.

In the second set of analyses, we use data at the patent-level (with patent-year observations). The goal of these analyses is to track the effect of the patent pledge on patent trading in a more detailed and direct manner and to test the impact on building upon the subsequently created external knowledge (Hypothesis 3), by examining the pledged patents and their spillovers, e.g. citing patents, in comparison to similar non-liberated patents and the latter's spillovers. In these difference-in-differences analyses, we compare the pledged patents, i.e. treated group, to a selected group of similar patents, i.e. control group, which we construct by matching each pledged patent with other patents using a text matching algorithm to measure technological similarity, following Arts, Cassiman, & Gomez (2017). We ask for a minimum similarity score of 15% and require the control patents to have the same filing year and to belong to the same technological class.

[13] The choice of the 200 patents allows us to avoid losing technological classes that have a substantial absolute number of IBM patents, however, a smaller percentage than 2.5%.

Eventually, we are left with 1351 patents in the control group with an average of about three control patents for each patent in the pledge[14]. These treated and control patents represent the "Initial" patents illustrated in Figure 2.

For each group (i.e. treated and control), we extend the number of patents by considering their spillovers, which we capture with "Level-one" and "Level-two" patents (see Figure 2). To do so, we draw on prior studies that argue for the proximity between citations and knowledge flows, despite possible noisiness[15] (Jaffe, Trajtenberg, & Fogarty, 2000; Duguet & MacGarvie, 2005; Gay & Le Bas 2005), and use *initial* treated and control patents' forward citations to proxy related knowledge flows (i.e. spillovers). Importantly, we differentiate between direct and indirect citations received by the *initial* patents. A patent that cites any of the initial patents (treated or control) represents a direct citation. We refer to this patent as *level-one* patent. Accordingly, depending on whether the level-one patent cites the pledged patent or a control patent, we consider it as treated or control, respectively. Further, a patent that cites the patent citing any of the initial patents (level-one patent) represents an indirect citation. We refer to this patent indirectly citing an initial patent as *level-two* patent (Figure 2 provides a graphical representation of the discussion above)[16]. This distinction between *level-one* and *level-two* patents is especially relevant for testing our third hypothesis, where we look at whether an external patent (i.e. a patent that was not created by IBM) is more likely to be cited by IBM (*level-two*) if that patent (external *level-one*) has built

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[14] Note that there are duplications in the control patents for the treated patents (i.e. two different pledged patents can share the same control patent).

[15] The noisiness of this measure (using forward citations to capture knowledge flows) is mostly related to the fact that during the patent application process, citations from patent examiners, who are responsible for checking for prior art, may be added to the original references in the patent application. However, citations are still a valid empirical proxy, especially in industries, where knowledge creation is cumulative, and are widely used in extant related literature.

[16] Although intuitively, indirect citations are not limited to only level-two patents (they can include patents at level three and more), for methodological reasons associated with the data characteristics, we consider only up until the patents in the second level. However, we believe that this restriction should not distort our results, as the higher the so-called level of the citation, the farther and less related, in principle, the newly created knowledge from the original invention in the focal patent. And what we are interested in capturing, are the "relevant" knowledge flows.

upon any of IBM's pledged patents after 2005. As for Hypotheses 1 and 2, we test for whether being related to the pledge (*level-one* or *level-two* patents in the treated group), increases the likelihood of being traded by IBM. Not surprisingly, then, in the analyses related to Hypothesis 1 (selling) at the patent-level, we limit the sample to only IBM patents.

Insert Figure 2 about here.

1.3.2 Pledged patents

Before we turn to data description and results discussion, we further examine the differences between the pledged and control patents (at the initial level), to corroborate the suitability of our empirical exercise. In their study on the effect of IBM 2005 patent pledge on new product introductions, Wen et al. (2016) compare the patents in IBM's pledge to a randomly selected group of similar patents in the market and conclude that the pledged patents have, in general, similar backward and forward citations, and that the pledged patents have lower number of claims. Similarly, they compare the pledged patents to other IBM patents, and find that the pledged patents have similar forward citations, but lower backward citations (indicating lower derivativeness) and lower claims (indicating narrower scope). In the current study, we compare the patents in the pledge (500 patents) to the control group (1351 patents). Table 1 presents our own tests of the differences between the treated and control groups in terms of the following observables: *Forward citations*, *Forward citations up to 2005*, *Backward citations*, *Non-patent references*, *Claims*, *and Independent claims*. Both groups of patents seem to have received a similar number of *Forward citations* and *Forward citations before 2005* and they both seem to have relied on a similar number of references. On the other hand, the patents in IBM's pledge seem to use more non-patent references, which suggests more closeness to science and a higher level of basicness. Our control group has a higher number of claims, similar to Wen et al. (2016), and a higher number of independent claims, which indicates a wider scope of knowledge. Overall, this evidence also rules out the argument that IBM could have pledged patents that were not valuable[17].

Insert Table 1 about here.

1.4 DATA AND METHODS

1.4.1 Data

To build the variables related to patent trading (i.e. selling and buying) activities, we rely on the Patent Assignment Dataset (PAD) from the United States Patent and Trademark Office (USPTO) website (www.uspto.gov). Importantly, unlike licensing or alliance transactions, most patent ownership transfers are recorded by parties with the database, since legally, for the (re)assignment to be considered as legally binding[18], it has to be filed with the USPTO. A typical transaction includes information on the buyer and the seller, the dates of recording, executing or signing, the number of patents/patent applications transacted per assignment, and the assignment type (Marco et al., 2015). Although the majority of the reassignments constitute an inventor-to-employer transfer of rights, we mainly consider inter-firm assignments of patents, as the latter are more reflective of markets for technology. Other types of patent reassignments that we do not consider as a buying or selling activity include name correction, government interest, and name

[17] Similar to the patent-level comparisons, Ayvazyan & Matr (2019) compare the treated and control groups in terms of the amount of patents by IBM and the total number of patents in the technological classes and do not find any drastic differences in the trends before 2005.

[18] Marco et al. (2015) note that whether the recorded transfers accurately represent the population of the assignments remains an open question, since it is not mandatory to record the transfer of patent rights at the USPTO. However, interested parties do have incentives to record an assignment with the USPTO, as only those patent transfers that are recorded serve as evidence of ownership transfer in courts.

change of the assignee. Since the assignee names are not disambiguated in the Patent Assignment Database, we follow the name standardization procedure from the NBER patent data project[19] to identify possible IBM transactions. Finally, after identifying the bought and sold patents, we are able to link these data with other relevant data on patent characteristics from the USPTO database PatentsView[20] that we use to construct our independent and control variables. This data is disambiguated for patents, inventors, assignees (firms/individual inventors).

1.4.2 Empirical Model

For the class-level analyses, we run the regressions under the specification of a linear estimator:

$$Y_{jt} = \alpha + \beta\ Openness_{jt} + \delta\ Openness_{jt} * After\ 2005_{j} + \mu * Controls_{jt} + u_j + \mu_t + \varepsilon_{jt},$$

where j indicates the technological class, and t indicates time. For the error components, u_j indexes a technological-class-specific effect and ε_{jt} is an idiosyncratic error term. Our baseline regressions take the relevant trading intensity as dependent variables (Y_{jt}). We regress these variables on the degree of openness of IBM in the corresponding technological class, as measured by the class' presence in the patent pledge. To capture the extra effect of the decision of opening up this knowledge, we interact the openness measure with a dummy variable for the years from 2005 to 2010. This approach involves a difference-in-differences with a non-dichotomous treatment variable (*Openness*) and dichotomous time variable (*After 2005*). In order to accurately estimate the precision of the regression coefficients, we cluster the standard errors at the level of the treatment assignment, technological class level. Since the variable Openness is time invariant, adding it as an explanatory variable is equivalent to adding the group means of this variable as a separate predictor. This approach is similar to the correlated random effects approach of Mundlak

[19] Available at **https://sites.google.com/site/patentdataproject**.
[20] Available at **www.patentsview.org**.

(1978). Moreover, we add to the model year fixed effects to control for the time trends in a flexible manner.

We use an analogous setting for the patent level analysis, where the openness measure is captured with a dichotomous indicator (*Pledge-Related Patent*[21]) denoting if the focal patent cites any pledge patent, directly or indirectly. In these patent-level analyses, we use a difference-in-differences design with dichotomous treatment group and dichotomous treatment time and with standard errors clustered at the patent level.

1.4.3 Dependent Variables

IBM Selling $_{Class}$ and IBM Buying $_{Class}$. We build these variables for our class-level analyses (see Identification Strategy subsection above), to account for patent acquisitions in a specific technological class in a specific year. As noted previously, when identifying patent acquisitions, we exclude within-firm reassignments of rights – recorded reassignments from an inventor employee to an employer assignee (Employee Assignments) or reassignments due to changes in the assignee name or name corrections –, in addition to agreements of governmental interest. By verifying whether IBM is on the buying or selling side of the patent trade, we determine the number of patents sold or bought in each of the transactions, and then aggregate these values per year at the technological-class level. Hence, *IBM Selling $_{Class}$* (*IBM Buying $_{Class}$*) represents the total number of patents that IBM sold (bought) in a specific technological class in a given year. In some analyses, we also include the variable *IBM Trading $_{Class}$*, which we create by summing up the yearly bought and sold patents by IBM per technological class, to account for the firm's aggregate participation in markets for technology.

[21] For variable descriptions, see Table 1.

IBM Selling $_{patent}$ and IBM Buying $_{patent}$. In the analyses at the patent level, our dependent variables related to the participation in markets for technology, are (binary) dummies that simply record whether IBM bought or sold the focal patent in a given year.

Citations from IBM. We build the variable *Citations from IBM* at the patent-level to test our third hypothesis. This is a yearly measure, counting the number of citations made by IBM to level-one patents. To construct this variable, for each level-one patent in a given year, we simply aggregate the total citations received from IBM.

1.4.4 Independent Variables

Openness. As remarked in our empirical model, the effect of outbound openness at the technological-class level, is captured by the interaction term between an openness measure, *Openness*, and the dummy *After 2005*. The variable *Openness*, represents the claims-weighted count of the pledged patents in each of the technological classes[22]. Weighting these patents by their number of claims, rather than simply using patent counts, allows us to better reflect on the scope/breadth of the opened-up knowledge in technological classes (Allison, Lemley, Moore, & Trunkey, 2004; Novelli, 2015). Accordingly, the technological classes without any pledged patents obtain a value of zero in their openness score.

Pledge-related Patent. To account for "openness" in our patent-level analyses, we create the (binary) dummy variable *Pledge-related Patent*, which indicates whether the patent is a level-one or level-two citation to any of the initial 500 pledged patents. In some cases (for Hypothesis 3),

[22] This approach is similar to Wen et al. (2016) measure of openness, called "Commons".

we specify *Pledge-related Level-one Patent* to refer to the level-one pledge-related patent (i.e. taking a value of 1 if the level-one patent is pledge-related, and 0 otherwise).

In Table 2, we describe all the variables used in our analyses at both levels.

Insert Table 2 about here.

1.5 RESULTS

1.5.1 Descriptive Statistics

Descriptive statistics for selected variables at the class level appear in Panel A in Table 3. For our sample period between 1999 and 2010, we have 1969 class-year observations belonging to 177 technological classes, in total, 50 out of which were to some extent opened up due to IBM's pledge in 2005. The average *Openness* score in our panel data is 80.5 claims and the maximum score is 2184 claims. On average, IBM files for 118 patents yearly in the average technological class with a maximum of 2020 patents in a class. The average technological class has 19045 patents yearly from all the firms in the market. From the same class in the same year, IBM buys slightly more than 11 patents, on average, while it sells around 24 patents. In Panel A in Table 4, we present the statistical correlations between our main variables at the technological class level. Analogously, Panels B in Tables 3 and 4 show the descriptive statistics and the correlation matrix, respectively, for the main variables at the patent level.

Insert Tables 3 and 4 about here.

Further, we provide some simple and preliminary statistics, exploring the differences between the pledge-related patents that IBM sold and bought in our sample, to get some initial insights on the characteristics of the patents in IBM's trading decisions. We compare these two groups of patents, 549 sold and 453 bought patents, in terms of observables, like patent's *Forward Citations*, *Backward Citations*, *Non-patent References,* and *Independent Claims* (see Table 5). While the forward citations received by the bought patents seem to be higher than the ones received by the sold patents, in terms of the backward citations, both groups seem to be statistically similar. The two groups seem to be statistically similar also in terms of the number of the *independent claims*, indicating that these patents seem to have similar breadths/scopes. More interestingly, the difference in *Non-patent References* is extremely statistically significant, where, on average, the bought patents have higher numbers of non-patent references. In later analyses, we notice that the buying probability increases when the patent has more non-patent references, yet the opposite happens for the selling probability in the corresponding model (see Table 7).

Insert Table 5 about here.

The pre- and post-trends of IBM's participation in markets for technology, in terms of patent buying and selling activities in opened-up (treated) versus close (control) technological classes are shown in Figure 3. This figure suggests that IBM's decision to open up its IP strategy was associated with an increased buying and selling tendencies in the opened-up technological classes. Arguably, the figure provides a preliminary support for the use of difference-in-differences analyses in our empirical approach, pointing out at acceptably similar pre-treatment trends for both variables of interest. Interestingly, one can note that the association between IBM patent trading and openness may seem to be lagged. We speculate that these "lagged" effects can be explained by the time that may be needed for the pledge to facilitate a market creation, which will in turn enable IBM to buy (sell) subsequent inventions from (to) others. In other words, time is needed for the demand and supply of technology to be developed so that IBM can internalize the externalities of its strategic openness. Our additional analyses (see Results section below) formally test for this effect over time. Taken together, these graphs suggest that IBM's trading in markets for technology experienced a boost after the firm's decision to adopt outbound open innovation, as proxied by employing the 2005 patent pledge.

Insert Figure 3 about here.

1.5.2 Class-level Results

We begin with investigating how the aggregate trading activities of IBM are associated with the variation in its strategic shift toward openness. Then, we study how *IBM Selling* $_{Class}$ or *IBM Buying* $_{Class}$ change with the openness level. Table 6 reports the main results for this part of the analysis. The positive and significant coefficient of the interaction term in column (1) in Table 6 suggests that additional 100 claims in an opened technological class are associated with 3.7 extra traded patents, either bought or sold, in that technological class after the pledging time, year 2005[23]. Column (2) indicates that the total number of patents sold by IBM after 2005 in affected technological classes, increases by 1.6 patents with each additional 100 claims contributed to the pledge. Analogously, the third column shows that the number of patents that IBM buys also increases with the firm's outbound openness. More specifically, IBM buys 0.4 patents per class with an increase of 100 claims to the openness of the technological class. The second and third

[23] Considering that each pledged patent includes, on average, 16.72 claims, this numbers imply that, on average, one more pledged patent leads to 0.61 additional traded patents.

models point at the direction that IBM gets more involved in trading activities, in general, after its decision to waive its exclusivity rights of its intellectual assets. However, IBM seems to be keen on selling more patents in comparison to buying patents. In relative terms, a one-standard-deviation increase in *Openness* leads, on average, to a 0.053 (80×0.016/24) standard-deviation increase in selling and a 0.03 (80×0.004/11) standard-deviation increase in buying after 2005. These findings provide support for our Hypotheses 1 and 2.

Insert Table 6 about here.

1.5.3 Patent-level Results

To investigate the effect of the patent pledge on IBM's behavior in markets for technology in a more direct way (for the first two hypotheses), we conduct patent-level analyses, where we check for the likelihood of a patent being sold or bought by IBM (*IBM Selling $_{Patent}$* or *IBM Buying $_{Patent}$*), depending on whether or not the patent is related to the pledge. We construct two different samples of patents to study the buying and selling possibilities separately. The sample for testing the probability of buying consists of both the level-one and level-two patents (both the pledge-related and control patents). For the analysis of the probability of selling, we build the sample from IBM's level-one and level-two (both treated and control) patents. The effect of interest is represented by the interaction term between the dummies *Pledge-related Patent* and *After 2005*. We control for citations received by the patent (*Forward Citations*), since that can be a signal of quality and potentially can increase the probability of being traded. Other controls are *Backward Citations*, *Non-patent References*, and *Independent Claims*, which can account for the patent scope and value. In addition, we control for the total number of patents IBM files in the focal patent's technological class (*IBM Total Patents $_{Class}$*). The results in column (2) in Table 7 imply that after 2005, IBM is significantly more inclined to sell patents that are related to the pledge. The probability of IBM selling a patent increases after 2005 by 0.02% for the pledge-related patents. Column (4) shows that being related to the pledged patents does not seem to affect the probability of being bought by IBM. Overall, the results presented in Tables 6 and 7 give a strong support for our first hypothesis and a partial support for the second one.

Insert Table 7 about here.

To test Hypothesis 3, which states that the focal firm internalizes the knowledge created by other players through building upon it, we analyze the effect on *Citations from IBM* to level-one patents before and after the practice of strategic openness. To do so, we first identify the pledge-related and the corresponding control group of level-one patents (*Pledge-related Level-one Patent*), after which we simply distinguish between whether or not the level-one patent belongs to IBM (*Non-IBM Level-one Patent*). The idea behind these classifications is to allow for empirically testing whether IBM will build upon the external subsequent knowledge more, in comparison to its own subsequent knowledge, which we will be able to capture by interacting the dummies *Pledge-related Level-one Patent, Non-IBM Level-one Patent*, and *After 2005*. Table 8 comprises a three-way interaction approach with the corresponding two-way interaction terms. We are particularly interested in the coefficient of the interaction term between *Level-one Pledge-related Patent* and the *After 2005* dummy, as well as in the three-way interaction term. The first of these two coefficients of interest is negative and statistically significant, suggesting that IBM depends less on its own level-one pledge-related patents after 2005 in comparison to non-pledge-related ones (i.e. level-one control patents). More interestingly, the three-way interaction is significantly positive, which means that IBM seems to internalize the spillovers created by others using its liberated knowledge more than it uses its own subsequent knowledge. Taken together, these results provide evidence to confirm our third hypothesis positing that the opening up firm will draw on the knowledge others create using its opened-up knowledge.

Insert Table 8 about here.

1.5.4 Robustness Checks and Additional Analyses

The potential confounding effect of OIN. In 2005, IBM, Novell, Philips, Red Hat, and Sony launched the Open Invention Network (OIN) with the aim to advance Linux and other OSS programs. To become a member of this network, firms are required to offer their patents for royalty-free licenses and agree not to assert their own patents against the Linux innovators. The patents that OIN acquires from the outsides are also offered royalty-free to the members. This way, OIN's goal is to create a collaborative ecosystem, a patent-non-aggression community and protect its members from litigation and other types of patenting risks (OIN official website[24]). Since both the creation of OIN and IBM's patent pledge took place in 2005, and both events represented a liberation of knowledge for the OSS community, one could argue that the results presented earlier in the paper could be driven by the launch of the shared defensive patent pool, OIN, rather than IBM's pledge. Therefore, it is reasonable to address the potential confounding effect of the OIN's establishment on IBM's internalization strategies after 2005.

In order to do so, we follow a similar approach used for our (original) *Openness* measure and create the variable *OIN Openness* at the class level, to capture the knowledge scope/breadth liberated by OIN in each of the technological classes. More specifically, this measure indicates the

[24] **https://www.openinventionnetwork.com/**

claims-weighted patent count of OIN patents related to a technological class *j*. While OIN owns more than 1300 global patents, we only consider the 660 patents registered at the USPTO when constructing our proxy.

To disentangle the impact of the OIN launch from IBM patents' pledge, we run the main analyses with incorporating *OIN Openness*. In particular, in models (1), (3), and (5) in Table 9, we examine the effect of *OIN Openness* isolated from IBM's pledge, while in models (2), (4), and (6), we consider both events simultaneously. We perform these analyses for the main variables of interest regarding IBM's trading activities. The results show that the effect of the patent pledge is robust to accounting for the impact of OIN liberated patents. In models (1), (3), and (5), *OIN openness* seems to have no effect on the number of patents IBM sold, bought, or traded, respectively, after 2005. More importantly, the effect of *Openness* on the variables of interest in models (2), (4), and (6) does not seem to change when considering *OIN openness*, which provides additional evidence that the 2005 patent pledge influences the changes in the firm's behavior in markets for technology and its effect does not seem to be mixed with the effect of OIN launch.

Insert Table 9 about here.

The development of the openness effect over time. During our sample period, IBM did not add to the 500 patents in the pledge after 2005, which means that the shock was unstaggered and concentrated in the few years after 2005. To study the development of the effect of IBM's pledge over time in more details, we break down the effect over the years following the firm's decision. In our sample, there are five years after the announcement of the patent pledge, 2005-2010, with the first (second) block of analysis being the years 2006 and 2007 (2008 and 2009), and the last one, being the year 2010. For all of these blocks, we create dummy variables, each of which we interact with the openness measure. We do this to reflect on the concentration of the effect of openness, in terms of the closeness from the shock. The results in Table 10 show that the effect of the patent pledge on the variables of interest related to trading is concentrated in the second block, years 2008 and 2009. Overall, these results may suggest that the impact of openness takes some time to show up in the firm's patenting and IP trading activities and fades away after a few years.

Insert Table 10 about here.

Economic effects. To get further insights on the economic effect of the patent pledge, we investigate the intensity of IBM's inventive activities, as proxied by the number of patents filed by IBM, and its ability to create radical inventions, proxied by the number of radical patents. To construct the latter variable, we follow Eggers & Kaul (2018) measure of radicalness. Both of these aspects can help quantify the economic returns to adopting an open IP strategy, as these have been positively linked to firm value, firm future earnings, etc. (e.g. Mitchell, 1989). The results in Table 11 show that IBM experienced an increase in its inventive output in the technological classes, proportionally to their degree of openness. Analogously, the radicalness of IBM's patents also increased after the firm's decision to open up its IP strategy. An increase in a specific technological class openness by 100 claims is associated with an increase in the number of patents produced by IBM by 9.64 patents and 0.8 more radical patents after the firm's shift toward openness in 2005. This positive association between the adoption of an open IP strategy and the number of total patents and the number of radical patents can be an indicator of firm's value and its future earnings (Mitchell, 1989; Bessen, 2009).

Insert Table 11 about here.

1.6 CONCLUSIONS

Our paper sheds light on a new possible angle for investigating a firm decision to allow for inside-out knowledge flows for no direct financial benefits, i.e. strategic openness, prominent examples of which are patent pledges by various multinational giants. This behavior seems to contradict the traditional management theories that emphasize the role of ownership and protection of intellectual assets in ensuring value appropriation from the firm's innovation. In this paper, we study certain actions of a firm after its adoption of outbound open innovation, in order to improve our understanding of possible internalization mechanisms. Mainly, we claim that the firm can capitalize on the externalities resulting from its decision to grant free access for its knowledge to the outsiders through two channels. The first channel involves selling intellectual assets in markets for technology to meet the hypothesized demand resulting from the increased engagement of third parties in the liberated knowledge. The second one refers to bringing the subsequent external knowledge in-house via buying intellectual assets in markets for technology or building upon them internally. We test our hypotheses using IBM's pledge of 500 patents to the OSS community in 2005 during the period 1999-2010. Our results suggest that IBM exploited the markets for technology options in the research lines related to the liberated knowledge after its shift toward outbound openness via selling intellectual assets. In addition, IBM seems to have kept valuing the subsequent knowledge in the opened-up fields created by others, evidenced by increased building on external patents and by increased involvement in buying transactions of patents in markets for technology.

Overall, this study contributes to the literature on open innovation by investigating how firms may internalize on their practice of (non-pecuniary) outbound openness through the proposed two channels. To the best of our knowledge, we provide a novel link between open innovation and markets for technology. While prior research has proposed that outbound openness may trigger a demand boost in the firm's complementary assets (e.g. Alexy et al., 2018), in this paper, we show an augmented demand for the firm's other relevant knowledge, which can be met through markets for technology. However, one should also analyze the costs of this practice and the forgone opportunities that the firm could achieve if it did not decide to involve in this practice. Such costs and opportunities can be related to potential licensing revenues the firm could make or possible benefits from blocking potential competitors from using its knowledge.

Our study is subject to limitations. As we empirically examine the effect solely for IBM, the external validity of this study is limited, which means that one should be careful when implementing our findings in different contexts and for other firms. Nevertheless, we believe that studying a firm as big as IBM is still useful as a case from which other firms can learn. IBM is a big firm that provides a great variety for aspects to be explored and other firms thinking of adopting openness can infer a lot from it. These findings are expected to be more relevant and beneficial for firms with substantial resources and capabilities that allow them to employ the suggested mechanisms, especially in the markets for technology. Another related limitation for our study could be linked to the fact that we do not observe heterogeneity in terms of factors, such as firm's size and capabilities, financial and intellectual, which may be essential when deciding to open up the firm's IP strategy. Next, one other factor that we cannot account for due to our empirical setting, is the timing of openness adoption (e.g. earlier adopter vs follower) and how it could change the dynamics of our mechanisms. These could provide opportunities for future research. Finally, we assume that openness in one area of knowledge has no impact on the effect of openness in another knowledge area. Since the fields of knowledge can be interrelated and therefore, dependent on each other at different degrees, one can think of considering the interactions among classes' openness, especially the ones that are closely related to each other, for future research.

1.7 TABLES

Table 1: Tests of the differences between the treated and control groups of patents.

	Pledged Patents (500 patents)			**Control Group** (1351 patents)			**Difference**
VARIABLES	Mean (SE)	Min	Max	Mean (SE)	Min	Max	Mean (SE)
Forward Citations	39.900	1	357	36.621	1	540	3.278
	(6.230)			(1.449)			(2.771)
Forward Citations *up to 2005*	38.685	1	341	35.356	0	540	3.328
	(6.032)			(1.435)			(2.733)
Backward Citations	9.900	1	56	12.249	1	263	-2.349
	(0.994)			(0.469)			(1.210)
Non-patent References	3.510	0	177	2.723	0	107	0.787*
	(1.263)			(0.204)			(1.211)
Claims	16.724	1	57	19.583	1	120	-2.859***
	(1.440)			(0.359)			(1.341)
Independent Claims	3.594	1	17	3.905	0	28	-0.311***
	(0.323)			(0.073)			(0.630)

Note: The column "Difference" represents the value from subtracting the mean of the control group from the treated group of patents. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 2: Variable descriptions.

Variable name	**Variable description** *(all variables are yearly measures)*	**Level of analysis**
Dependent variables	***Data source*: Patentsview.org (patents, citations), USPTO (reassignments)**	
IBM Buying $_{Class}$	Number of patents IBM buys in a given technological class.	*Class*
IBM Selling $_{Class}$	Number of patents IBM sells in a given technological class.	*Class*
IBM Trading $_{Class}$	Number of patents IBM buys or sells in a given technological class.	*Class*
IBM Total Patents $_{Class}$	Number of patents that belong to IBM in a given technological class.	*Class*
IBM Rad. Patents $_{Class}$	Number of radical patents (following Eggers & Kaul (2018)) that belong to IBM in a given technological class.	*Class*
IBM Buying $_{Patent}$	A level-two patent that is bought by IBM.	*Patent*
IBM Selling $_{Patent}$	A level-two patent that is sold by IBM.	*Patent*
Citations from IBM	Number of citations each level-one patent receives from IBM.	*Patent*
Independent variables	***Data source:* Patentsview.org (patents, citations)**	
Openness	Summation of the claims of the patents that were pledged by IBM in a given technological class in 2005.	*Class*
After 2005	1 if the (application) year (of the patent) is after 2005, 0 otherwise.	*Both*
Total Patents $_{Class}$	Number of patents in a given technological class.	*Class*
Number of Patenting Firms $_{Class}$	Number of firms that patent in a given technological class.	*Class*
Pledge-Related Patent	Pledge-related level-one or level-two patent (binary).	*Patent*
Pledge-Related Level-one Patent	Pledge-related level-one patent (binary).	*Patent*
Non-IBM Level-one Patent	1 if the level-one patent does not belong to IBM (binary).	*Patent*
Patent age	The difference between the application year and the given year.	*Patent*
Forward Citations	Number of forward citations received by the patent.	*Patent*
Backward Citations	Number of backward citations made by the patent.	*Patent*
Claims	Number of claims of the patent.	*Patent*
Independent Claims	Number of independent claims of the patent.	*Patent*
Non-patent References	Number of backward citations made by the patent to references that are not patent.	*Patent*

Note: This table describes the variables at class- and patent-levels used in our analysis.

Table 3: Descriptive statistics of the main variables at the class and patent levels.

VARIABLES	Mean	Std. Dev.	Min	Max
A.		**Class-level**		
Openness	80.560	267.172	0	2184
IBM Total Patents $_{Class}$	118.294	225.438	1	2020
IBM Selling $_{Class}$	24.043	72.601	0	2468
IBM Buying $_{Class}$	11.280	22.466	0	511
Total Patents $_{Class}$	19045.890	18759.940	35	96356
Number of Patenting Firms $_{Class}$	288.825	274.233	1	1639
VARIABLES	Mean	Std. Dev.	Min	Max
B.		**Patent-level**		
IBM Buying $_{Patent}$	0.0004	0.020	0	1
IBM Selling $_{Patent}$	0.0005	0.023	0	1
Forward Citations	22.980	45.442	1	1083
Backward Citations	35.423	53.281	1	500
Non-patent References	10.627	17.676	0	100
Claims	23.717	16.924	1	539
Independent Claims	3.737	2.744	0	136

Note: Panel A includes the descriptive statistics of the variables defined at the class level. The number of class-year observations is 19,045. Panel B includes the descriptive statistics of the variables defined at the patent level. These statistics consider both the level-one and level-two patents. *IBM Buying* $_{Patent}$ and *IBM Selling* $_{Patent}$ are binary variables. The number of patent-year observations is 308,307. All variables are defined in Table 2.

Table 4: Correlation matrix for the main variables at the class and patent levels.

	VARIABLES	1	2	3	4	5	6	7
	A.				**Class-level**			
1	Openness	1						
2	IBM Total Patents $_{Class}$	0.374	1					
3	IBM Selling $_{Class}$	0.025	0.101	1				
4	IBM Buying $_{Class}$	0.225	0.240	0.184	1			
5	Total Patents $_{Class}$	0.157	0.661	0.192	0.383	1		
6	Number of Patenting Firms $_{Class}$	0.118	0.354	0.153	0.395	0.843	1	
	VARIABLES	1	2	3	4	5	6	7
	B.				**Patent-level**			
1	IBM Buying $_{Patent}$	1						
2	IBM Selling $_{Patent}$	0.165	1					
3	Forward Citations	-0.005	-0.006	1				
4	Backward Citations	-0.006	-0.008	0.096	1			
5	Non-patent References	-0.005	-0.008	0.056	0.540	1		
6	Claims	0.003	0.000	0.149	0.102	0.120	1	
7	Independent Claims	-0.001	0.001	0.103	0.023	0.038	0.450	1

Note: Panel A includes the correlations between the variables defined at the class level. Panel B includes the correlations between the variables defined at the patent level. All variables are defined in Table 2.

Table 5: Comparisons between the pledge-related bought and sold patents by IBM.

VARIABLES	Mean		Std. Dev.		Min		Max	
	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy
Forward Citations	24.290	30.320	34.690	57.150	1	1	265	800
Backward Citations	16.880	47.290	18.070	62.030	1	1	234	323
Non-patent References	5.610	27.290	16.700	71.190	0	0	355	360
Independent Claims	3.620	3.790	2.340	2.490	0	1	22	20

Note: This table provides the preliminary statistics of the patents that IBM bought and sold during the sample period. All variables are defined in Table 2.

Table 6: IBM's total traded patents and total bought and sold patents in each technological class.

VARIABLES	(1) IBM Trading $_{Class}$	(2) IBM Selling $_{Class}$	(3) IBM Buying $_{Class}$
Openness	0.154	0.103***	0.018
	(0.257)	(0.010)	(0.011)
After 2005	-0.340*	0.280	-0.305
	(0.138)	(0.698)	(0.241)
After 2005 x Openness	0.037***	0.016**	0.004***
	(0.009)	(0.008)	(0.001)
Total Patents $_{Class}$ (×1000)	0.540	-0.096	0.006
	(1.150)	(0.087)	(0.031)
Number of Patenting Firms $_{Class}$	0.003*	-0.002	-0.002
	(0.001)	(0.008)	(0.002)
IBM Total Patents $_{Class}$	-0.015	0.007	0.015
	(0.014)	(0.010)	(0.009)
Year and Tech. class FE	Yes	Yes	Yes
Constant	-0.834***	-0.669	0.281
	(0.620)	(0.618)	(0.247)
Observations	1,969	1,969	1,969
Number of Tech. classes	177	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 7: The effect of being related to the pledged patents on the probability of IBM selling or buying.

VARIABLES	(1) IBM Selling $_{Patent}$	(2) IBM Selling $_{Patent}$	(3) IBM Buying $_{Patent}$	(4) IBM Buying $_{Patent}$
Pledge-Related Patent		0.035***		0.005***
		(0.003)		(0.000)
After 2005		-0.086***		-0.004***
		(0.002)		(0.000)
Pledge-Related Patent x After 2005		0.008**		0.0001
		(0.004)		(0.001)
Forward Citations (×1000)	0.488***	0.268***	0.019***	0.009***
	(0.023)	(0.029)	(0.003)	(0.003)
Backward Citations (×1000)	0.029***	-0.075***	-0.007***	-0.007***
	(0.010)	(0.011)	(0.000)	(0.000)
Independent Claims (×1000)	1.950***	1.110***	0.004	-0.006
	(0 200)	(0. 193)	(0.046)	(0.047)
IBM Total Patents $_{Class}$ (×1000)	-0.001***	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Non-patent References (×1000)	-0. 361***	-0. 265***	0.007**	0.006**
	(0.019)	(0.018)	(0.003)	(0.003)
Constant	-0.006***	0.000	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Year and Tech. class FE	Yes	Yes	Yes	Yes
Observations	181,794	181,794	263,215	263,215

Note: This table provides the estimates based on the patent-level analyses under the specification of a random-effect linear estimator. The sample in columns (3) and (4) consists of IBM patents only, hence, the difference in the number of observations. Robust standard errors clustered at the patent level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 8: IBM citations to the patents created using the pledged patents (level-one patents).

VARIABLES	(1) Citations from IBM	(2) Citations from IBM	(3) Citations from IBM
Pledge-related Level-one Patent		0.060	-0.030
		(0.039)	(0.066)
Non-IBM Level-one Patent		-0.034	-0.147***
		(0.039)	(0.053)
After 2005		0.0261	0.281**
		(0.069)	(0.126)
Pledge-related Level-one Patent x Non-IBM Level-one Patent			0.194**
			(0.082)
Pledge-related Level-one Patent x After 2005			-1.088***
			(0.162)
Non-IBM Level-one Patent x After 2005			-0.039
			(0.148)
Pledge-related Level-one Patent x After 2005 x Non-IBM Level-one Patent			0.958***
			(0.203)
Patent Age	0.093***	0.092***	0.091***
	(0.007)	(0.008)	(0.008)
Forward Citations (×1000)	7.430***	7.430***	7.430***
	(0.746)	(0.746)	(0.747)
Backward Citations (×1000)	6.910***	6.890***	7.000***
	(0.276)	(0.277)	(0.277)
Independent Claims (×1000)	-2.720	-2.780	-3.120
	(5.940)	(5.940)	(5.940)
Non-patent References (×1000)	7.430***	7.430***	7.430***
	(0.746)	(0.746)	(0.747)
Year and Tech. class FE	Yes	Yes	Yes
Constant	1.948***	1.932***	1.984***
	(0.088)	(0.097)	(0.099)
Observations	48,051	48,051	48,051
Number of level-one patents	16,773	16,773	16,773

Note: This table provides the estimates based on the patent-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the patent level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 9: The effect of IBM's patent pledge when considering the effect of OIN patents.

VARIABLES	(1) IBM Selling $_{Class}$	(2) IBM Selling $_{Class}$	(3) IBM Buying $_{Class}$	(4) IBM Buying $_{Class}$	(5) IBM Trading $_{Class}$	(6) IBM Trading $_{Class}$
Openness		0.009***		0.004		0.013**
		(0.003)		(0.003)		(0.006)
OIN Openness	-0.003	-0.005	-0.003	-0.003	-0.005	-0.007
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
After 2005 x Openness		0.003**		0.003*		0.005**
		(0.001)		(0.001)		(0.002)
After 2005	-0.089	-0.181*	-0.052	-0.145	-0.142	-0.325*
	(0.080)	(0.096)	(0.067)	(0.100)	(0.138)	(0.179)
After 2005 x OIN Openness	0.001*	-0.0004	0.001	-0.007	0.003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Total Patents $_{Class}$ (×1000)	-0.023	-0.021	0.030	0.032	-0.007***	-0.006***
	(0.035)	(0.035)	(0.023)	(0.024)	(0.001)	(0.001)
Number of Patenting Firms $_{Class}$	0.001	0.001	-0.001	-0.002	0.000	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
IBM Total Patents $_{Class}$	0.005	0.004	0.007	0.005	0.011	0.009
	(0.005)	(0.005)	(0.005)	(0.004)	(0.009)	(0.009)
Year and Tech. Class FE	YES	YES	YES	YES	YES	YES
Constant	-0.0772	0.0425	-0.226	-0.106	-0.304	-0.0631
	(0.109)	(0.0967)	(0.190)	(0.132)	(0.293)	(0.215)
Observations	1,969	1,969	1,969	1,969	1,969	1,969
Number of Tech. classes	177	177	177	177	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological-class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

Table 10: The development of the openness effect over time after the pledge.

VARIABLES	(1) IBM Selling $_{Class}$	(2) IBM Buying $_{Class}$
Openness	-0.001	-0.001
	(0.003)	(0.003)
Years 2006&2007 x Openness	0.002	-0.001
	(0.002)	(0.000)
Years 2008&2009 x Openness	0.006***	0.008**
	(0.002)	(0.003)
Year 2010 x Openness	-0.000	-0.000
	(0.000)	(0.000)
Total Patents $_{Class}$ (×1000)	-0.028	0.017
	(0.031)	(0.015)
Number of Patenting Firms $_{Class}$	0.001	-0.002
	(0.002)	(0.001)
IBM Total Patents $_{Class}$	0.002	0.004
	(0.004)	(0.003)
Year and Tech. Class FE	Yes	Yes
Constant	0.109	0.0558
	(0.091)	(0.093)
Observations	1,969	1,969
Number of Tech. Classes	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological-class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

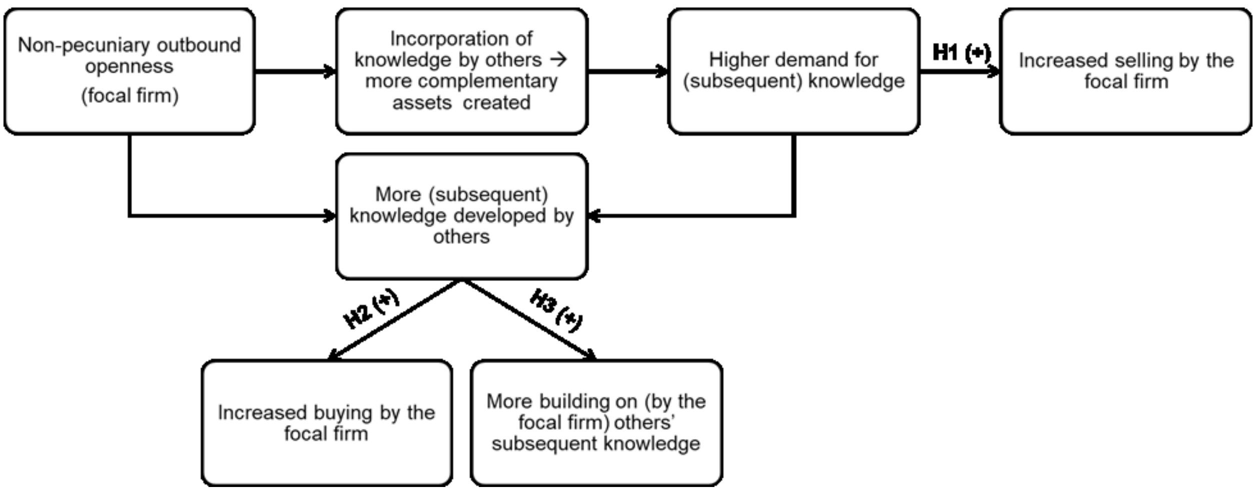
Table 11: IBM's total patents and total radical patents in each technological class.

VARIABLES	(1) IBM Total Patents $_{Class}$	(2) IBM Rad. Patents $_{Class}$
Openness	0.960***	0.018***
	(0.082)	(0.006)
After 2005	-12.450*	-1.618***
	(7.342)	(0.593)
After 2005 × Openness	0.096***	0.008**
	(0.037)	(0.003)
Total Patents $_{Class}$ (×1000)	-6.170***	0.102***
	(1.190)	(0.033)
Number of Patenting Firms $_{Class}$	0.426***	-0.005**
	(0.010)	(0.002)
IBM Total Patents $_{Class}$		0.064***
		(0.006)
Year and Tech. Class FE	Yes	Yes
Constant	8.537	0.890*
	(8.456)	(0.475)
Observations	1,969	1,969
Number of Tech. Class	177	177

Note: This table provides the estimates based on the class-level analyses under the specification of a random-effect linear estimator. Robust standard errors clustered at the technological-class level are presented in brackets. All variables are defined in Table 2. ***1% significance, **5% significance, *10% significance.

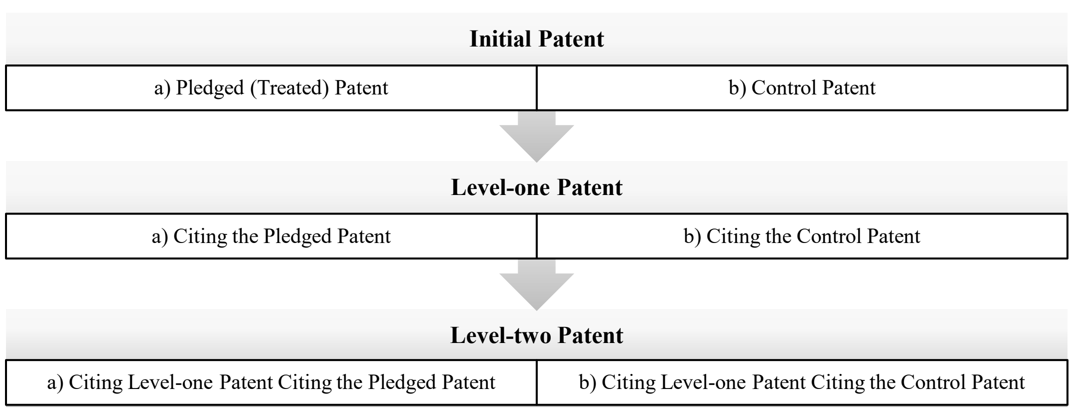
1.8 FIGURES

Figure 1**:** Consequences of the focal firm's adoption of outbound openness.



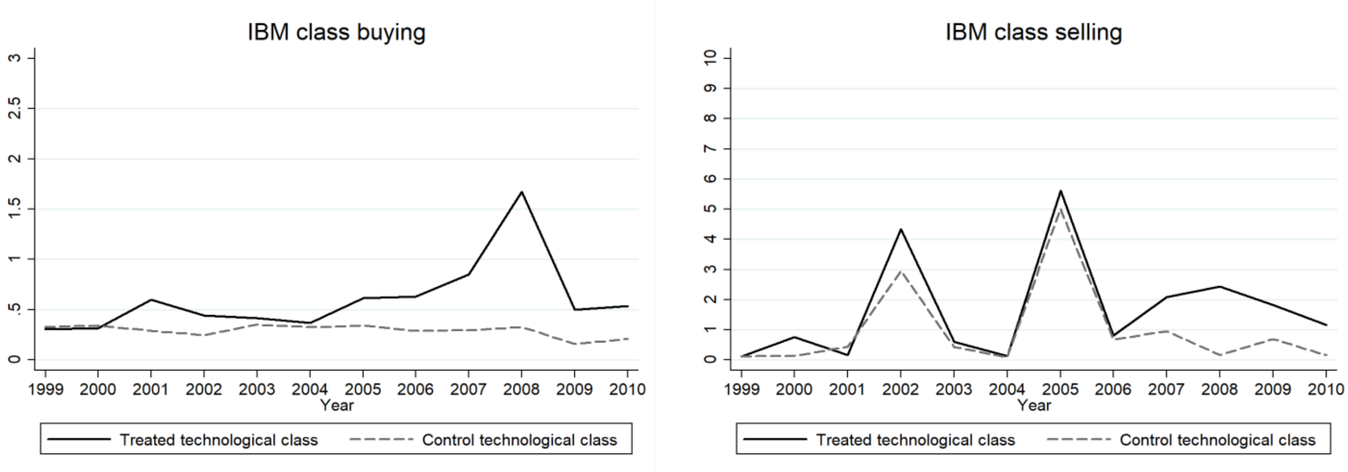
Note: This figure summarizes the three hypotheses developed in the paper.

Figure 2**:** Illustration for the levels of patents.



Note: This figure depicts the discussion on the use of the pledged 500 patents for the construction of treated and control groups for patent-level analyses. The matching procedure is performed at the initial step, where we match the pledged patents (i.e. treated) with a randomly selected group of non-pledged patents that comply with certain criteria (i.e. control), according to textual similarity scores between the pledged and non-pledged patents' abstracts, their application years and technological classes. In the next two steps, we create "Level-one" and "Level-two" patents, according to the citations received to the pledged (or pledge-related, i.e. the left side of the figure) and initial control (or initial-control-related; the right side of the figure) patents.

Figure 3: Average Number of Patents Bought/Sold by IBM from 1999 to 2010 for the Treated vs Control Technological Classes.



Note: A technological class is considered as treated (control), if it includes (does not include) a patent that was opened-up by IBM in 2005. In addition, the control group of technological classes is restricted to those, where IBM had patented in significantly before 2005. IBM class buying (selling) represents the average number of patents bought (sold) in all the treated/control technological classes.

Chapter 2

How Outbound Open Innovation Strategies Affect the Subsequent Innovation Process in the Technology Field: Evidence from IBM's Patent Pledge

2.1 INTRODUCTION

Recently, the prevalence of open innovation has increased as a model for organizing firm's innovation processes. As emphasized by Chesbrough, Vanhaverbeke, & West (2006, p.1), "open innovation is the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively". Much of the previous literature on the topic has focused on the "outside-in" knowledge flows (i.e. "inbound open innovation"), studying advantages and disadvantages of using external knowledge sources on such organizational outcomes, as firm performance (Kafouros & Forsans, 2012), innovation performance (Laursen & Salter, 2006), or new product introductions (Rubera, Chandrasekaran, & Ordanini, 2016). Yet, practicing open innovation also implies pecuniary or non-pecuniary "inside-out" knowledge flows (i.e. "outbound open innovation"), where the firm sells or reveals its proprietary knowledge to the outside world (Dahlander & Gann, 2010).

Despite the relatively low level of attention received so far from scholars (West & Bogers, 2014), the latter type of outbound openness, where firms do not seek for direct financial benefits, has become a subject of growing interest among researchers, given its seemingly counterintuitive nature and the increasing number of practices (e.g. patent pledges, granting access to specific research tools, etc.) in various industries in recent years. Not surprisingly, many of the works on the non-pecuniary outbound openness have tried to explain its determinants and the potential firm-level consequences (e.g. Levin et al., 1987; West, 2003; Alexy & Reitzig, 2013; Contreras, 2015; Alexy et al., 2018; Matr & Ayvazyan, 2019), whilst discussing channels of appropriation from such decisions. However, there has been quite little empirical analysis of the plausible implications at a more aggregated level than the firm, the knowledge domain level[25]. And these "systems" (i.e. fields of knowledge), in which firms are embedded, are likely to be affected, with the switch toward more freely accessible knowledge available for external actors (West, Vanhaverbeke, & Chesbrough, 2006).

Aiming at filling in this gap, in this paper, we study the consequences of a firm decision to adopt non-pecuniary outbound openness in its intellectual property (IP) strategy (henceforth, outbound openness[26]) on the innovation amount and type subsequently generated, market structure characteristics, and on markets for technology. In particular, in addition to asking (i) whether more knowledge is subsequently created, we ask whether (ii) more radical knowledge is developed, (iii) more participants innovate in or enter the opened-up knowledge fields, and whether (iv) more trading activities occur in the markets for technology. These are all closely relevant questions, the analysis of which at the level of the knowledge area, can improve our understanding of the strategic value of outbound open innovation in terms of its proclivity towards innovation advancement and innovation management. Empirically, we test our hypotheses for the sample period of 1999-2010 via a "difference-in-differences" approach, utilizing the patent pledge of IBM in 2005 as a shock for outbound openness. In this pledge, IBM made 500 of its patents covering various fields of knowledge available for free to the Open Source Software (OSS) community and assured not to pursue anyone for the usage of the opened-up knowledge for infringement (IBM announcement, 2005).

Our findings suggest that the larger IBM's contribution to the knowledge fields is (i.e. the higher the level of "openness" of the knowledge fields is), the more knowledge, thereafter, is

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[25] We further relate our study to two of the papers that do provide a discussion on the topic: Wen et al. (2016); Murray et al. (2016).

[26] "Outbound open innovation", "outbound openness", "strategic openness", and "inside-out open innovation" are used as synonyms in this paper.

created in these domains and that this new knowledge tends to be more radical in nature. The plausible cause behind the surge in generating new knowledge is related to the increased demand for further knowledge developments and the reduction in the access costs due to outbound openness (e.g. Chesbrough, 2003; Boudreau, 2010; Wen et al., 2016; Matr & Ayvazyan, 2019). In the same vein, our results support the conjecture that openness encourages other entities to get more involved in the opened-up areas of knowledge, which, in turn, gives rise to more possibilities for knowledge recombination, hence, more radical knowledge creation (Nelson & Winter, 1982; Fleming, 2001; Ahuja & Lampert, 2001; Jung & Lee, 2016). The trend, however, is channeled through an increase in the involvement of existing actors, since the number of new contributors into the knowledge field does not seem to be significantly altered. We explain this finding from the perspective of the need of having certain "absorptive capacities" (Cohen & Levinthal, 1989, 1990; Zahra & George, 2002) to be able to develop on the opened-up knowledge. Finally, we show that transactions of intellectual assets in the markets for technology increase proportionally to the level of openness in the areas of the liberated knowledge, pointing to a greater reliance on external technological solutions for (at least) some industry players. We build on the argument that outbound openness likely reduces the uncertainty of the commercial value of the liberated and related technologies, through a combination of increased inventive output and increased engagement from market actors in developing follow-on knowledge.

The main contribution in this paper is to provide an empirical insight on the phenomenon of inside-out open innovation, by considering its repercussions for the innovation-related outcomes in the knowledge domains. At this level of analysis, to the best of our knowledge, this is the first empirical study linking the literature on open innovation with that on markets for technology[27].

[27] While Matr & Ayvazyan (2019) link these two streams of literature at a firm-level analyses, we explore the relationship at the knowledge domain level.

Overall, our evidence suggests that openness in the knowledge fields may facilitate the specialization of the technology suppliers (West et al., 2016) and stimulate the knowledge markets, as supported by the increased number of contributors to developing knowledge internally and of buying transactions of externally developed knowledge. This may ultimately improve the match between innovations and firms that lies at the heart of the paradigm of open innovation research (Chesbrough, 2003).

Our study also complements the findings of two pieces of related recent work. One of them is Wen et al. (2016) showing that following the practice of strategic openness, start-up firms introduce more new products. Though we draw on the authors' empirical context to capture the levels of openness (i.e. utilizing IBM's patent pledge), rather than focusing on the commercialization aspect, in the present paper, we establish a positive link of the pledge with the knowledge creation facet, evidenced by a subsequently increased inventive output in the opened-up knowledge domains. Thus, an implication of the current study could be relevant for regulators and policy makers to consider promoting firms to practice outbound openness as a means to boost inventive activities in knowledge domains. Another set of our results is comparable to the ones from Murray et al. (2016), who analyze the consequences of outbound openness in a setting of academic researchers, mainly biologists, in pharmaceutical fields. The authors hypothesize and find that lowering access costs to existing research tools encourages scientists to create more knowledge and explore more novel research directions[28]. However, there are two main differences between Murray et al. (2016) and our study. First, our empirical setting is distinct in terms of the

[28] Murray et al. (2016) empirical context includes the National Institutes of Health agreements with DuPont in the late 1990s to waive the access costs to specific research tools important for research advancements, genetically engineered mice.

industry (pharma vs software) and the type of the innovations (academic vs corporate[29]) in focus. Second, though our findings are similar in regard to the amount and type of the inventive output, the subtle difference is that we observe an increase in the quantity of radical inventions in the opened-up knowledge fields, while Murray et al. (2016) find that new lines of research are created due to openness. This may also explain the finding from our study that outbound openness in our context does not attract actors that do not have previous experience in the liberated fields of knowledge (new-to-the-field actors). Altogether, these differences emphasize the value added by studying the effect of openness in firm's IP strategy at the knowledge domain level.

2.2 THEORY AND HYPOTHESES

The premise of this paper is that the switch from a traditional closed IP strategy, - where a firm highly relies on internal R&D processes and tends to protect its knowledge from the outsiders by various means, - toward outbound open innovation may have implications not only for the firm engaged, but also for the systems that the firm is part of, such as networks, sectors or industries (West et al., 2006). The scope of our research includes (a) the non-pecuniary type of outbound openness, - defined as the flows of knowledge or resources from the inside to the outside environment, where the firm does not pursue direct or immediate financial benefits (Dahlander & Gann, 2010), - and (b) the area of knowledge to which the opened-up knowledge belongs. In the following subsections, we link openness in the knowledge domains to innovation-related outcomes of interest, and illustrate the relationships in Figure 1.

Insert Figure 1 about here.

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[29] The academic innovations in Murray et al. (2016) are captured by the citations received from researchers or institutions. Meanwhile, our paper captures corporate inventions using patent data.

2.2.1 The Effect of Outbound Openness on the Subsequent Innovations and Market Structure

Inventive output and inventing participants. The first relationship that we consider is the one between openness and the subsequent inventive activities in the knowledge fields. Prior studies postulate that by lowering the costs of entry for outside parties, openness encourages their involvement to the opened-up knowledge fields, thereby driving more innovative output. Consider the case of an external party that is well equipped with (or can develop) complementary downstream resources that can help with commercializing the opened-up knowledge. For this market player, the transaction costs of identifying or acquiring the otherwise proprietary knowledge, the potential costs of inventing around or infringing on that knowledge would decrease, with more knowledge freely available due to outbound openness. For instance, Wen et al. (2016) posit that these cost reductions induce new product introductions by startups in the opened-up knowledge fields. Arguably, then, with more involvement from such innovators, the demand for further knowledge in the area will increase.

Now, consider the case of an external party that is keen on developing technology. On the one hand, with more knowledge revealed or made freely available in the knowledge field, these market players will encounter less constraints for advancing the opened-up pieces of knowledge. On the other hand, the reduced barriers may contribute to the emergence of a dominant design (Boudreau, 2010), which can ultimately affect the future of the knowledge field (Bower & Christensen, 1995). Therefore, for technology developers, engaging in the opened-up knowledge domains may also become a strategic necessity for keeping their competitiveness. Taking into account this, together with the potentially increased demand in the field for related knowledge, in their study on the plausible implications of outbound openness for the focal firm's internalization mechanisms, Matr

& Ayvazyan (2019) assume that the amount of follow-on inventions and external parties involved in the opened-up areas of knowledge will also tend to increase. However, the authors do not provide an empirical examination of the link. And despite the positive evidence from other contexts, as such, the pharmaceutical industry (Murray et al., 2016) or platform openness (Parker & Van Alstyne, 2017[30]), we believe that it is essential to empirically test whether the effects would also hold in the setting of a purely outbound open innovation. Overall, the intuition behind the reduced incorporation costs and the arguments related to the increased demand for inventive output lead us to hypothesize that more participants will invent in the opened-up fields and more knowledge will be created in those fields:

Hypothesis 1 (H1): The more openness introduced in the area of knowledge, the more knowledge is created in that area of knowledge.

Hypothesis 2a (H2a): The more openness introduced in the area of knowledge, the more participants invent in that area of knowledge.

New-to-the-field participants. The next logical step is to understand whether the increase in the number of participants comes from new-to the field entrants versus existing firms in the industry. Noteworthy to mention that exposure to external knowledge is not a sufficient condition for a firm to benefit from it. Because of the cumulative nature of the innovation process and the need for specific resources and capabilities to be able to transform new inventions into

[30] Parker & Van Alstyne (2017) introduce a sequential innovation model for innovation decisions that a platform holder may face, particularly, how much open the platform should be and how long it will take for follow on innovations to fold back into the platform. In the model, the platform sponsor seeks to receive benefits from developers in return to giving away internal resources. These benefits come in the form of royalties that developers have to pay and eventually owning innovations that are built by them (the developers eventually lose their innovations). Overall, the authors argue that openness in platforms stimulates third-party developers to build upon the opened up knowledge, even in the presence of royalty fees and losing their IPs. In contrast, the concept of pure outbound openness implies that developers (innovators) do not need to pay royalties or give up the innovations that they build using the opened up knowledge. Given this, we expect that outbound openness is likely to encourage other market players to build upon the opened up knowledge.

commercializable outcomes, not every actor in the market would promptly start inventing and contributing to the innovation output in a new-to-the-firm domain. Cohen & Levinthal (1989, 1990) are the first to define the concept of absorptive capacity (AC) as a firm's "ability to recognize the value of new information, assimilate it, and apply it to commercial ends". Zahra & George (2002) review the AC concept and differentiate between two types of absorptive capacities: potential AC and realized AC, which separate the acquisition and assimilation components of the construct from the transformation and exploitation ones, respectively. They state, "Exposure to diverse sources does not necessarily lead to PACAP [potential AC] development, especially if these sources have low knowledge complementarity with the firm" (Zahra & George, 2002, p.193). From the findings of increased number of product introductions from startups (Wen et al., 2016), one could expect that the number of new-to-the-field participants would also increase. However, since new product development represents the commercialization part of the innovation process, we speculate that it is related to the realized AC. Meanwhile, knowledge creation would arguably require more science-related capabilities, which makes it more associated with the potential AC. In other words, the firm needs an existing know-how in the field in order to be able to use the liberated technologies to create new knowledge. Therefore, we anticipate that a firm without an existing set of absorptive capacities will be less willing or less able to get involved in the areas of liberated knowledge, if these knowledge fields are unknown to the firm[31]. Taking into account these arguments, we hypothesize:

Hypothesis 2b (H2b): The more openness introduced in the area of knowledge, the proportion of new-to-the-field out of total participants decreases.

[31] By "unknown to the firm", we mean that the firm does not have experience in the area of knowledge.

Radical innovations. The seminal work by Schumpeter (1934) emphasizes the role of innovation in bringing in economic change and surviving in an increasingly competitive milieu. Especially relevant is the role of radical innovations in firm survival and economic growth (Tushman & Anderson, 1986; Anderson & Tushman, 1990; Schumpeter, 1934). Radical innovations, together with incremental innovations constitute the two main types of innovations, classified by innovation literature (Gopalakrishnan & Damanpour, 1997). These innovations differ in their degree of novelty in technology, require different capabilities for creation and implementation, and have different consequences for firms (Dewar & Dutton, 1986). In contrast to incremental innovations, which introduce minor changes in existing technology (Damanpour, 1991; Munson & Pelz, 1979), radical innovations represent major departures from current practice (Duchesneau, Cohn & Dutton, 1979; Ettlie, 1983; Dewar & Dutton, 1986). While the chances of success are not high in the case of radical innovations, the rewards are substantial in case of success, in comparison to incremental innovations that require less effort, but lower rewards in terms of performance implications (Schumpeter, 1942; Marsili & Salter, 2005). At a broader level, radical innovations that often require large investments in R&D, may result in new products, change the market structure or even create new markets (Levinthal & March, 1993). We further hypothesize whether or not the exposure to more knowledge for outside parties via outbound openness, may translate into more radical or incremental knowledge creation in the field.

The usage of external sources may facilitate firms to combine and create various technologies and new knowledge (Nelson & Winter, 1982). Dependent on how intensively firms draw on external sources of innovation, they may create innovations with different degrees of novelty. Laursen & Salter (2006)[32] suggest that firms' relying *deeply* on a few external sources of

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[32] The authors explain that in the case of radical innovations, firms tend to focus on a narrow range of sources in the earlier stages of the lifecycle (Rothwell et al., 1974; Urban & von Hippel, 1988). In contrast, they tend to develop

innovation favors radical innovations. Meanwhile, relying *broadly,* yet less intensively, on a greater number of external sources of knowledge favors incremental innovations. Connecting the concept of outbound openness to the depth of knowledge, we argue that the more a firm opens up in a specific area of knowledge, the more deeply others have the opportunity to draw upon that knowledge. To put it differently, with more knowledge liberated in an area of knowledge, a firm has the possibility to rely more intensively on this specific area of knowledge. Hence, we expect that more radical innovations will be created in a knowledge field due to strategic openness.

Further, on the one hand, radical innovations naturally involve a high level of uncertainty and complexity, which increases the need for more information and actors involved in the innovation processes (Murray et al., 2016; Eisenhardt & Tabrizi, 1995). Not surprisingly, the complexity and uncertainty inherent to radical innovations are also associated with increased lead-time necessary for their development (Kessler & Chakrabarti, 1999). On the other hand, as we hypothesize, outbound openness increases the chances of getting more participants involved in creating knowledge, via reducing access costs. This, in turn, allows for more possibilities for knowledge recombination. Following the logic from innovation recombination scholarship (Fleming, 2001; Nelson & Winter, 1982; Ahuja & Lampert, 2001; Jung & Lee, 2016), combining new knowledge with existing knowledge leads to the generation of more radical inventions. Finally, as argued by O'Connor (2006), outbound openness may also facilitate the processes and reduce the time necessary for radical innovation development. Thus, given the availability of more freely accessible information, commitment from more inventors and shortened time required for invention, due to strategic openness, the latter is likely to contribute to more radical knowledge creation in the field. Hence, we hypothesize:

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incremental innovations when a dominant design has already emerged and there are manifold options available for improvements (Abernathy & Utterback, 1975; Utterback, 1994).

Hypothesis 3 (H3): The more openness introduced in the area of knowledge, the more radical knowledge is created in that area of knowledge.

2.2.2 The Effect of Outbound Openness on the Markets for Technology

Markets for technology are well known for providing firms with the possibility of acquiring/in-licensing externally developed or selling/out-licensing internally developed knowledge assets. The effect of the strength of IP protection has been argued in some studies to lead to more transactions in markets for technology, while other studies have argued for the opposite effect on activities in these markets (Arora & Gambardella, 2010). In this subsection, we view knowledge liberation as a means of relaxing IP protection, and hypothesize that, paradoxically, it leads to an increase in trading in technology markets.

Arora & Gambardella (2010) claim that, in addition to information asymmetries and moderating transaction costs, the uncertainty about the commercial value of a technology plays a significant role in the demand for the technology. We expect that the uncertainty in the value of technology will decrease in the presence of outbound openness, through increased inventive output and number of contributors in the area of knowledge. Reasonably, an increasing number of inventing firms in a specific field may signal an attractive business opportunity with lower risks. Therefore, for inventors that prefer technology outsourcing to in-house technology development, as a faster and safer way to innovate and market a technology (Veugelers & Cassiman, 1999), there are more possibilities for exploiting the "buy" option in more open knowledge fields. This becomes feasible as outbound openness arguably fastens the innovation processes and increases the number of participants. Another argument is related to the proposition that outbound openness encourages (at least some) outsiders to carry on more R&D activities. Considering that opening up offers others with more freedom to external knowledge sources (West & O'Mahony, 2008), thereby boosting their in-house R&D activities, and the premise that in-house R&D helps firms to benefit from external knowledge (Escribano, Fosfuri, & Tribó, 2009), we expect outbound openness to also indirectly increase the demand for external knowledge sources. Empirical evidence provides support for this notion, indicating that in-house R&D facilitates the replication of knowledge (Tsai, 2001), and assists firms in benefiting from external knowledge (Escribano et al., 2009).

On the supply side in the markets for technology, Arora, Fosfuri, & Gambardella (2004) claim that technology markets are generally characterized with less competition, in comparison to product markets. We expect that with even higher competition in the downstream product markets due to outbound openness (e.g. Wen et al., 2016), certain groups of inventors, especially the technology specialists, using Arora & Gambardella (2010) terminology, will be encouraged to invent technologies in order to sell them in the technology markets (as hypothesized above). Consequently, we expect that the effect of strategic openness on the technology market size is positive:

Hypothesis 4 (H4): The more openness introduced in the area of knowledge, the more trading activities of intellectual properties takes place in that area of knowledge.

2.3 RESEARCH SETTING

To investigate the effects of outbound openness on a field of knowledge in terms of the subsequent knowledge characteristics and its production patterns, the structure of contributors, and trading activities, we exploit IBM's significant shift toward openness in the IP strategy through its patent pledge of 2005, as an exogenous shock for the openness of the knowledge domains. Accordingly, we track the relationships of interest before and after 2005 for the period 1999-2010. IBM's announcement claimed that the firm was granting royalty-free access to key knowledge pieces covered by 500 software patents to the community of OSS. Despite the fact that various other events before 2005 could be argued to have facilitated the switch from a traditional closed to an open innovation regime at IBM (e.g. taking the initiative to create the software Apache or the integrated software development community Eclipse), this patent pledge was considered to be by then the biggest commitment to the OSS community in terms of inside-out knowledge flows. The patents in the pledge covered a variety of software markets, allowing us to have a sufficient amount of heterogeneity in the openness levels of the knowledge fields for observing changes in the outcomes of interest over time. In addition, given that the estimated cost of patenting typically ranges around $20000 for a U.S. patent, the monetary value of the pledge could reach about $10 millions. Before proceeding to the description of data, sample and variable construction methods using the 500 pledged patents, we briefly discuss two main reasons for why IBM's pledge provides an appropriate context for testing our hypotheses.

Our first argument is related to the plausible exogeneity of IBM's pledge for the outsiders in our empirical exercise. Since we are interested in the implications of the pledge for the knowledge fields (with higher versus lower levels of openness), rather than IBM itself, we argue that the probability that the external players could have anticipated this decision is fairly low. Prior research that used this shock to measure openness at both the firm (e.g. Matr, 2019; Matr & Ayvazyan, 2019) and industry levels (Wen et al., 2016), has thoroughly discussed the motivations behind the pledge. Among other motives, the latter has been linked to IBM's competition with Microsoft, the lawsuit against Santa Cruz Operation (SCO) Group, and favoring the patentability of software inventions in Europe. Therefore, for the purposes of our paper, utilizing this pledge to measure the openness levels of the knowledge domains should not raise serious endogeneity concerns. To further strengthen our effects and rule out other possible similar concerns, we repeat all our analyses, excluding IBM's patents from the samples (see section Results).

The second reason for why we believe that IBM's pledge represents a suitable context for our main analyses, is related to the selection of the patents in the pledge. Since the construction of our so-called treated and control groups of knowledge domains depends on the pledged patents, it is essential to assure that the differences between these groups are minimal. To that end, in their study, Wen et al. (2016) performed comparisons according to certain observable patent characteristics between the 500 patents from the pledge and two other sets of patents. Comparing first with a group of patents from IBM's patent portfolio and then with non-IBM patents from the market, the authors conclude that the pledged patents did not entail drastic differences in terms of, for instance, forward and backward citations, and claims. Similarly, in Matr & Ayvazyan (2019), we compare the patents in the pledge to a set of other patents that we chose based on textual similarity in the patents' abstracts, and confirm that the pledged patents seemed to be similar to their comparable patents in terms of characteristics, such as forward and backward citations, non-patent references, claims, and independent claims. Overall, these observations suggest that the 500 liberated patents were financially valuable and fairly similar to their analogous patents. More importantly, the comparisons at the knowledge domain level presented in the next section are in line with the intuition that the current research context is appropriate for addressing the questions raised in this study.

2.4 DATA AND METHODS

We perform our main analyses at the knowledge domain level, represented by technological classes, according to The United States Patent Classification (USPC). We explore through these analyses the temporal variation in outcomes, such as the innovation output, innovation radicalness, new-to-the-field entries to the area of knowledge, and knowledge trading activities, using the openness level of the knowledge field. In total, each model comprises 177 classes, out of which, 50 classes include the pledged patents and represent our treated group. The classes without any pledged patent form the basis of our control group, which is defined by the classes, in which IBM had been active before 2005 and in which it could potentially have opened up some of its IP (Matr & Ayvazyan, 2019). In particular, we require significant contributions from IBM to these classes prior to 2005 in the form of having more than 200 patents or having a share of 2.5% of all the class patents. The comparisons between the treated and control technological classes in terms of the number of patent applications made solely by IBM (indicating IBM's inventive efforts in the field) and the ones made by all the firms in the class (indicating inventive activities in the field) are presented in Figure 2. This figure shows fairly similar before-2005 trends for the two groups of technological classes, which suggests that IBM does not seem to have chosen to pledge patents in fields of knowledge that were characterized with higher or lower inventive activities or in areas which IBM did not prioritize or was lowering its inventive efforts.

Insert Figure 2 about here.

To build our measures for innovation process characteristics, we use the patent and citation data from the United States Patent and Trademark Office (USPTO) database from PatentsView (www.patentsview.org), which is disambiguated for patents, inventors, assignees (individual inventors or firms). Furthermore, we utilize the Patent Assignment Dataset (PAD) from USPTO website (www.uspto.gov) to build variables related to the trading activities of patents. PAD includes all reassignment activities in the patent data due to different reasons. Mainly, we consider the inter-firm assignments of patents as an ownership exchange, since they capture transactions in the markets for technology more accurately than other types of assignments. The majority of the reassignments are employer assignments, which are an inventor-to-employer transfer of rights, and we do not consider them as trading activities. Name correction, government interest, and name change of the assignee are other types of patent reassignments that we exclude from our sample.

2.4.1 Variables

Dependent variables. We construct the variables *Total patents $_{class}$*, *Total assignees $_{class}$*, *Total traded patents $_{class}$*, by aggregating the number of patents, assignees (i.e. participants), and traded patents, respectively, per technological class per year. The variable *New-to-the-field entrants $_{class}$ (%)* represents the ratio between those assignees that have not patented in the technological class up until the given year and the total number of assignees in the class. As for accounting for the radicalness of the subsequently created patents, we follow Eggers & Kaul (2018) method and create the variable *Radical patents $_{class}$*. This measure considers patents that are novel and that can potentially create radical technology. By novel, we refer to “new-to-the-field” inventions, and not “new-to-the-firm” ones. These inventions reflect what prior literature has called “unprecedented combinations” (Nahapiet & Ghoshal, 1998; Rodan & Galunic, 2004), meaning that they draw upon knowledge that no or few inventors have used in the technological field prior to the year of invention. Empirically, we compare each patent’s backward citations (indicating the existing knowledge that the patent builds upon) to the citations of all the other patents that are filed in the same technological class, in order to ultimately track how potentially “new” the focal patent’s knowledge recombination is. We then assign a score of radicalness to each of the patents and create a binary dummy variable for whether the patent’s score is above the 90th[33] percentile, following

[33] The results hold when repeating the relevant analyses for considering 85th and 95th percentiles.

the steps from Eggers & Kaul (2018)[34]. Finally, at the class level, for each technological class, we build *Radical patents* $_{class}$, taking the summation of the binary values in the class.

Openness. To build our independent variable, following the method from Wen et al. (2016) for constructing the measure "Commons," we first count the number of claims of the patents (indicating knowledge score/breadth) that were pledged by IBM in 2005. Then, at the technological class level, we aggregate those values and for each class, get a claims-weighted patent count. If there are no pledged patents in the technological class, it obtains an openness score of zero. We believe that using this measure, instead of simply adding up the number of patents that were pledged in each technological class, better represents the class' scope of openness, as patent claims reflect the coverage of specific elements in the inventions (Cohen & Lemley, 2001) and the latter's value (Allison et al. 2004, Bessen 2008).

In Table 1, we describe the rest of the variables used in our analyses.

Insert Table 1 about here.

2.4.2 Analytical Approach

In our models, we regress the response variables of interest at the technological class level on the class' degree of openness and estimate the following linear model:

$$\boldsymbol{Y_{jt} = \alpha + \beta\ Openness_j + \delta\ Openness_j * After\ 2005_j + u_j + \varepsilon_{jt},}$$

where (Y_{jt}) represents the dependent variables in the technological class j, and year t. $Openness_j$ measures the extent of the presence of the technological class j in the patent pledge, as explained above. The effect of outbound openness, the main effect of interest, is captured by the interaction

[34] See Eggers & Kaul (2018) for more details on the construction of this measure (specifically, the variables *LINK* (citation level), *DISTANT* (patent level), and *RADICAL* (patent level).

term between the openness measure and the dummy variable *After 2005*, taking a value of 1 for the years 2005-2010, and 0 for years 1999-2004. Our empirical models, thus, represent a difference-in-differences design, which includes a continuous treatment. For the error components, u_j captures an class-specific effect and ε_{jt} is an idiosyncratic error term. Finally, our models include year fixed effects and clustered standard errors at the level of technological class level, the source of variation.

2.5 RESULTS

Table 2 presents the descriptive statistics for the main variables in our analyses. There are 2116 class-year observations for our sample period between 1999 and 2010. In total, there are 177 technological classes, out of which 50 were opened up due to IBM's pledge in 2005. The average technological class has around 19000 patents, and about 80 of those, on average, are radical. This is consistent with the intuition from prior work that radical innovations occur less frequently than incremental innovations. The participants in the class annually trade, on average, almost 600 patents. The correlation matrix among the main variables is presented in Table 3.

Insert Tables 2 and 3 about here.

Before presenting the main results from our regression analyses, we provide some descriptive evidence in Figure 3, which presents the dynamics of our main dependent variables in knowledge domains (technological classes) characterized by high and low openness[35]. The figure demonstrates that after the patent pledge of 2005, there is a substantial growth (slight decline) in the total number of a) patents, b) different assignees, c) radical patents, in technological classes

[35] We consider a technological class as having a high (low) openness if it is among technological classes with the highest (lowest) ten openness measures.

with a high (low) level of openness. In contrast, there is little decrease in the number of new-to-the-field entrants in the technological classes characterized by high openness, while the decline is considerable in classes with low openness. As for the trading activities, classes with both high and low levels of openness experienced an increase in the number of traded patents, but the increase in classes with a high openness score seems to have been substantially larger. Though these graphs provide preliminary evidence for our hypotheses, we need to perform further analysis to confirm the results.

Insert Figure 3 about here.

2.5.1 Main Results

Table 4 reports how the number of participants (H2a) and new-to-the-field participants (H2b) are linked to strategic openness. The positive and significant coefficient of the interaction term in column (1) suggests that a one-standard-deviation increase in the openness of the technological class is associated with around 29 more assignees in that class after the pledge (approximately a 0.11-standard-deviation increase in assignees). Columns (2) and (3) in Table 4 show that the number of new-to-the-field entrants is not affected by outbound openness after the pledge, while the effect on the percentage of new-to-the-field entrants out of *Total assignees* $_{class}$ is negative and significant. Overall, these findings provide support for H2a and H2b.

Insert Table 4 about here.

Table 5 reports the results for the amount of the innovative output (H1), radical innovations created (H3) and trading activities (H4). The interaction term in column (1) is positive and significant, suggesting that a one-standard-deviation increase in the openness of the technological class is associated with 181 more patents in that class after 2005. Though the effect is modest, if one takes into account the average number of applications filed each year in each class (around 190,000), it is statistically significant. Further, the results in column (2) provide support for H3. In particular, as expected, the effects of the interaction term on the number of radical patents in the technological class are positive and significant at 1%. More specifically, a one-standard-deviation increase in the openness score of the technological class is associated with 15 more radical patents in that class after the pledge. Column (3) shows that the number of patents traded in the class are increasing with more openness introduced to the technological class. Analogously, an increase in the openness score of a technological class by one standard deviation is associated with 101 traded patents in that class after 2005. Overall, the findings in Table 5 are consistent with the intuition from H1, H3, and H4.

Insert Table 5 about here.

2.5.2 Robustness Checks and Additional Analysis

Innovation volume, type and trading activities. The results in Table 5 are based on technological classes that include the patents from all the firms in those classes. To rule out the possibility that these results are driven by the fact that IBM's patents are included in the technological classes (especially taking into account IBM's leading position in terms of the number of patents received[36]), we perform the same analyses, but excluding IBM patents from the technological classes. Moreover, we test the results for patent trading, excluding the trading

[36] Since 1992, IBM has been receiving the largest number of patents, and keeping its U.S. patent leadership for 25 years. For more details, see **https://www-03.ibm.com/press/us/en/presskit/42874.wss**.

activities where IBM is involved in, either as a seller or as a buyer. Similarly, this test aims to rule out the possibility that the trading boost after the pledge can be mainly driven by IBM transactions.

We define the dependent variables regarding the total number of patents (*Non-IBM patents* $_{Class}$), the number of radical patents (*Non-IBM radical patents* $_{Class}$) and the number of traded patents (*Total non-IBM trading* $_{Class}$) in a similar manner as the original variables (see Table 1). The results in Table 6 indicate that the effect of openness on the number of patents that do not belong to IBM is positive and significant at 1% significance level. In more details, a one-standard-deviation increase in the openness of the technological class is associated with 113 more patents being filed in that class after 2005. Similarly, the coefficient of the interaction term is positive and significant for the number of radical patents that do not belong to IBM, meaning that increasing openness by one standard deviation is linked to 12 more patents that are radical and that are not filed by IBM. The results in column (3) support the proposition that the trading activities witnessed an increased after IBM decision to liberate 500 patents, with and without considering IBM's trading activities. Overall, these findings confirm that the results in Table 5 do not simply represent IBM's presence in the knowledge domains, and that others in the industry are also affected by strategic openness.

Insert Table 6 about here.

Patent-level analyses. The results in Tables 5 (columns (2) and (3)) and Table 6 (columns (2) and (3)), show that the opened-up technological classes experienced a rise in the number of radical patents (H3) and trading activities (H4). Accordingly, one would expect that at the patent level, the pledge will generate spillovers in terms of radical knowledge and that these products of the spillovers will be particularly likely to be traded. To test this possibility and to provide more support for our H3 and H4, in a different set of analyses, we build our sample at the level of patent (with patent-year observations), following the method from Matr & Ayvazyan (2019). We construct the control group of patents (initial control group) for the 500 pledged patents (initial treated group) by matching each pledged patent with patents having similar abstracts following Arts, Cassiman, & Gomez (2017) approach of text matching. We also restrict the control group to patents from the same technological class and the same application year as the treated patent. Our control group consists of 1351 patents, including three control patents, on average, for each pledged patent. As citations are considered a common and valid way to capture relatedness and knowledge flows between patents (Jaffe, Trajtenberg, & Fogarty, 2000), we differentiate in the next step between direct and indirect citations received by the initial treated and control groups of patents. Specifically, a "level-one" patent is a patent that draws upon any of the treated or control initial patents, thus representing a direct citation. An indirect citation is captured by "level-two" patents that cite any of the level-one patents[37]. Overall, the intuition behind these analyses is that the knowledge flows, proxied by the direct and indirect citations, will be more radical in nature and will be more likely to be traded, if they are related to the pledged, rather than control group of patents.

Empirically, we replicate a similar model to the one estimated for the class-level analyses, where we construct our main independent variable capturing patent's openness, by identifying whether the patent is related to any of the pledged patents. We construct the dummy variable *Pledged-related patent*, taking the value of 1 if the patent represents a direct or an indirect citation to any pledged patent. Thus, the difference-in-differences design at this level includes a dichotomous treatment variable, where the dependent variables are the probability of level-one

[37] For a more detailed description of the sample construction at the patent level, see Matr & Ayvazyan (2019).

and level-two patents being radical, and the probability of them being traded. The linear model we estimate is as follows:

$$Y_{jt} = \alpha + \beta \text{ Pledge-related patent}_j + \delta \text{ Pledge-related patent}_j * \text{After } 2005_j + u_j + \varepsilon_{jt},$$

Table 7 reports how outbound openness affects the radicalness of the subsequent inventions at the patent level. *Pledge-related patent* in column (1) is restricted to level-one patents, and includes level-two patents in column (2). The coefficient of the interaction term for level-one patents' radicalness is insignificant, while the one for the radicalness of level-two patents is positive and significant ($p<0.01$). Numerically, an indirect citation to a pledged patent after 2005 is more likely to be radical in nature by 9%. Overall, these findings shed light into what kind of knowledge is subsequently created due to strategic openness. In particular, while we do not find evidence that the patents that directly cite the pledged patents are more radical if they cite after the pledge, we do find support that the patents with indirect citations (level-two patents) are more radical due to the pledge.

Insert Table 7 about here.

As an additional test for Hypothesis 4, in Table 8, we conduct a patent-level analysis to further explore the effect of outbound openness on knowledge markets. Specifically, we check for the likelihood of a patent being traded, depending on whether or not the patent is related to the pledge. We construct the sample pooling both the level-one and the level-two patents and, to determine traded patents at a given point in time, we match them with patents in the USPTO Patent Assignment Dataset. Thus, the dependent variable is a dummy, with a value of 1, if the patent is traded, and 0 otherwise. The variable *Pledge-related patent* in this table is made equal to zero for all the years before 2005 in order to account for the effect resulting from IBM's strategic openness.

As control variables, we include patent's forward citations (standardized by the application year and technological class), – which can be a proxy for the patent's quality, an important factor when it comes to trading a patent, – and the openness level of the patent's technological class. The results in column (1) show that being related to the pledged patents is associated with an increase of 6.8% in the probability of being traded. Analogously to the analysis in column (3) in Table 6, column (2) considers only those patents, where IBM is not a main party in the transaction. The results hold and economically, seem to be similar to those in the first column of Table 8, thereby confirming the intuition that the trading of the subsequently created patents was affected by the knowledge liberation. Untabulated results suggest that the effect on trading is mainly driven by the level-two patents, similar to the previous analyses on the radicalness of the subsequently created inventions. Mainly, these outcomes provide an additional and specific support for the argument that outbound openness enhances the volume of trading activities in the technology markets.

Insert Table 8 about here.

IBM's patent pledge and the launch of OIN. To rule out the possibility that the findings presented and discussed so far are confounded by the launch of the Open Invention Network (OIN) in 2005, we integrate the latter in our class-level analyses and present the results in Tables 9 and 10. OIN is an organization, established by big companies, such as IBM, Novell, Philips, Red Hat, and Sony, to provide the developers in the OSS community with protection and support for advancing OSS. One of the main functions of the OIN is buying patents that can potentially impose a litigation threat for the OSS inventors, and then providing these patents royalty-free for the organization members. To become a member of OIN, firms are obligated to grant free access to their OSS patents for the other members, and in return, are offered the option to use the other members' patents via cross-licensing.

Empirically, we create a variable capturing the magnitude of the knowledge liberated by OIN in each technological class, following a similar approach used to build our *Openness* variable (claims-weighted patent count). Columns (1), (3), and (5) in Tables 9 and 10, report the effect of OIN solely without the consideration of IBM's patent pledge. Meanwhile, Columns (2), (4), and (6) show the results, where both OIN launch and IBM's patent pledge are considered simultaneously. The results in Table 9 provide evidence that the positive effect of the patent pledge on the total number of participants found in our main analysis was not associated with establishing OIN, as the coefficient between *Openness* and *After 2005* does not seem to be affected by adding OIN into the analysis in model 2. We cannot make the same statement regarding the effect on *New-to-the-field entrants*, as it does not seem to be consistent for when we account for OIN's launch or consider the pledge only. However, the effect of the pledge on the new-to-the-field entries as a percentage out of the total number of participants remains negative, as shown in model 6, confirming the results from the main analysis. OIN seems to have had a negative effect on the rate of the new entrants. A possible explanation for this is that OIN was established to protect the active developers in the OSS community and not to encourage the inventors with no previous experience.

Insert Table 9 about here.

In Table 10, we replicate the results from Table 5 on the analyses of total patent applications, radical inventions, and patent trading, by adding the effect of OIN launch in the analyses. The results regarding the inventive output in the technological classes, in terms of its quantity and radicalness, seem to be uncontaminated by the contemporaneous event of lunching OIN, as shown in models 2 and 4. Though the effect of IBM patent pledge on the amount of trading activities at the class-level is not straightforward to disentangle from the effect of OIN (as both events seem to be intensifying the firms' tendency toward engaging in transactions in the markets for technology), the inclusion of the OIN in the analysis does not seem to change the direction of the effect of the pledge.

Insert Table 10 about here.

Outbound openness over time. In this subsection, we aim at getting more insights on the effect of openness on the main variables of interest, in terms of whether and how it changes over time after the shock. Similar to Matr & Ayvazyan (2019), we divide the period after the patent pledge in our sample period, 2006-2010, into smaller periods. More specifically, we gather the first two years after 2005 in one block, and the years 2008 and 2009, into a second block. Finally, the year 2010 represents the last block. We interact these periods with the openness measure to investigate the concentration of the effect over time. Table 11 demonstrates the results for this analysis and shows that the effect is fairly distributed over the three smaller periods, with being slightly intensified in the second period, years 2008 and 2009. Figure 4 provides a graphical representation of the effect of outbound openness over time on our response variables of interest. The separate figures provide support for our main findings on the effect of openness and are consistent with our analyses in Table 11.

Insert Table 11 and Figure 4 about here.

2.6 DISCUSSION AND CONCLUSIONS

Our paper sheds light on the relationship between strategic openness and the subsequent innovation process in the field of knowledge. Consistent with our hypotheses, the findings show that a substantial amount of liberated knowledge boosts up the innovation process at the knowledge domain level via increased innovative output, more novel knowledge created and more trading activities in markets for technology. Interestingly, our results regarding the effect of openness on the market structure characteristics contrast the ones from Murray et al. (2016). Specifically, we find that outbound openness encourages more participants to invent in the affected areas; however, this effect does not carry over into new-to-the-field entrants. The latter result contradicts the finding of Murray et al. (2016) and it seems to go against the open innovation premise of increasing access to new markets and reducing potential barriers to market entry. One possible explanation for these conflicting results is that the type of the opened-up knowledge might moderate the effect of outbound openness on the new-to the field entries rates. More specifically, according to Sosa (2009), R&D competencies can be application-specific (i.e. market-specific) and technology-specific (i.e. non-market-specific), dependent on whether these competencies can be used in one or multiple markets. One can expect that if the opened-up knowledge is related to application-specific competencies, it will increase market entries, because the liberated knowledge makes a significant difference in reducing access costs for new-to-the-field entrants, as noted by Murray et al. (2016). On the other hand, opened-up knowledge that is related to technology-specific R&D competencies would require new-to-the-field entrants to allocate substantial amount of efforts to transform it into knowledge that is applicable to a specific market. Consequently, one could expect that if the opened-up knowledge is associated with technology-specific competencies, it will not affect market entries, because the liberated knowledge would still exhibit uncertainty in making use of the knowledge.

This research provides insights for the policy makers on promoting the liberation of knowledge. Outbound openness has the potential to stimulate the innovation output at the knowledge domain-level and also it can improve the radicalness of the inventions created, which can help the products performances and the economic growth generally. However, outbound openness encourages the firms with existing know-how to get more involved in knowledge creation while it seems to discourage the new-to-the-field developers from entering new fields regardless of the knowledge availability. These consequences on the competition dynamics in the market should be considered in these situations. Furthermore, the knowledge liberation makes the markets for technology substantially more active, which improves the fit of the innovation and the firms, as well as incentivizes the specialization among firms in the supply and the demand sides. For future research, more dimensions can be considered to construct a wider picture of the effect of knowledge liberation. Factors, such as market shares and competition, entry of new markets, or other firms' tendency towards adopting outbound openness, are among the interesting repercussions to be studied.

2.7 TABLES

Table 12: Variable descriptions

Variable name	Variable description *(all variables are yearly measures)*	Level of analysis
Dependent variables	***Data source***: **Patentsview.org (patents, citations), USPTO (reassignments)**	
Total patents $_{Class}$	Number of patents in a given technological class.	*Class*
Total assignees $_{Class}$	Number of assignees/participants (U.S. and foreign firms, universities, individual inventors…) in a given technological class.	*Class*
New-to-the-field entrants $_{Class}$	Count of new-to-the-field assignees. An assignee is considered as new to the field if it is the first time for the assignee to patent in a given technological class.	*Class*
New-to-the-field entrants $_{Class}$ *(%)*	Proportion of *New-to-the-field entrants* out of *Total assignees*.	*Class*
Radical patents $_{Class}$	Value summation of the radical patents in a given technological class.	*Class*
Total trading $_{Class}$	Number of patents traded in a given technological class.	*Class*
Radical Level-one (Level-two) patent	1 if the level-one (level-two) patent is radical, 0 otherwise.	*Patent*
Traded patent	1 if the patent is traded, 0 otherwise.	*Patent*
Independent variables	***Data source:*** **Patentsview.org (patents, citations)**	
Openness	Summation of the claims of the patents that were pledged by IBM in a given technological class in 2005.	*Class*
After 2005	1 if the application year of the patent is after 2005, 0 otherwise.	*Class & Patent*
Pledged-related patent	1 if the patent directly or indirectly cites any of the 500 pledged patents of 2005 (i.e. is level-one or level-two), 0 otherwise.	*Patent*
Pledge related Level-one patent	1 if the level-one patent cites any of the pledged patents.	*Patent*
Pledge related Level-two patent	1 if the level-two patent cites any of the pledge related level-one (two) patents.	*Patent*
Patent age	The difference between the application year and the given year.	*Patent*
Patent standardized forward citations	Forward citations of the patent, standardized by technological class and year.	*Patent*

Note: This table describes the main variables used in this study.

Table 13: Descriptive statistics

VARIABLES	Mean	S.D.	Min	Max
Openness	80.171	266.586	0	2184
Total patents $_{Class}$	18954.589	18760.652	35	96356
Total assignees $_{Class}$	287.446	274.288	1	1639
New-to-the-field entrants $_{Class}$	114.546	111.037	0	713
New-to-the-field entrants $_{Class}$ (%)	0.405	0.116	0	1
Radical patents $_{Class}$	80.076	95.195	0	570
Total trading $_{Class}$	597.076	762.882	0	7500

Note: This table provides descriptive statistics on the main variables used in the current study. The variables are described in Table 1.

Table 14: Correlation matrix

	VARIABLES	1	2	3	4	5	6	7
1	Openness	1						
2	Total patents $_{Class}$	0.158	1					
3	Total assignees $_{Class}$	0.119	0.844	1				
4	New-to-the-field entrants $_{Class}$	0.150	0.762	0.962	1			
5	New-to-the-field entrants $_{Class}$ (%)	0.051	-0.187	-0.061	0.087	1		
6	Radical patents $_{Class}$	0.239	0.949	0.810	0.741	-0.160	1	
7	Total trading $_{Class}$	0.136	0.792	0.722	0.607	-0.235	0.777	1

Note: This table provides the correlation matrix among the main variables used in this study. The variables are described in Table 1.

Table 15: Outbound openness and market structure characteristics

VARIABLES	(1) Total assignees $_{Class}$	(2) New-to-the-field entrants $_{Class}$	(3) New-to-the-field entrants $_{Class}$ (%)
Openness	0.069	0.047*	4.60e-05**
	(0.058)	(0.027)	(2.16e-05)
Openness x After 2005	0.110***	0.033	-4.60e-05***
	(0.033)	(0.024)	(1.31e-05)
Constant	248.9***	111.5***	0.443***
	(19.48)	(8.576)	(0.008)
Year FE	YES	YES	YES
Observations	2,076	2,076	2,076
No of tech classes	177	177	177

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the total number of participants, new-to-the-field entrants, and the percentage of new-to-the-field entrants out of the total number of participants in the technological classes. The variables are described in Table 1. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 16: Outbound openness and inventive volume, type, and markets for technology

VARIABLES	(1) Total patents $_{Class}$	(2) Radical patents $_{Class}$	(3) Total Trading $_{Class}$
Openness	0.550*	0.057*	0.193
	(0.314)	(0.031)	(0.147)
Openness x After 2005	0.678***	0.056***	0.381***
	(0.180)	(0.017)	(0.139)
Constant	729.6***	64.1***	335.6***
	(68.970)	(6.227)	(32.560)
Year FE	YES	YES	YES
Observations	2,066	2,066	2,076
No of tech classes	177	177	177

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the total number of patents, radical patents, and traded patents in the technological classes. The variables are described in Table 1. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 17: Outbound openness and inventive volume, type, and markets for technology, technological classes without IBM patents

VARIABLES	(1) Non-IBM patents	(2) Non-IBM radical patents	(3) Total non-IBM Trading $_{Class}$
Openness	0.323	0.0389	0.163
	(0.229)	(0.0249)	(0.134)
Openness x After 2005	0.425***	0.048***	0.340***
	(0.122)	(0.014)	(0.127)
Constant	608.3***	57.68***	317.9***
	(54.150)	(5.509)	(30.240)
Year FE	YES	YES	YES
Observations	2,116	2,116	2,076
Number of tech classes	177	177	177

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the technological classes' total number of patents and radical patents that do not belong to IBM, and traded patents, where IBM is not a buyer or a seller. The variables are described in Table 1. Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 18: Relatedness to the pledged patents and the radicalness of the subsequent inventions

VARIABLES	(1) Radical Level-one patent	(2) Radical Level-two patent
Pledge-related patent	-0.029**	-0.009
	(0.012)	(0.021)
Pledge-related patent x After 2005	-0.010	0.090***
	(0.015)	(0.023)
Patent Age	0.015***	0.057***
	(0.002)	(0.003)
Constant	0.103***	0.333***
	(0.012)	(0.020)
Year FE	YES	YES
Observations	11,287	159,469
Number of patents	1,784	31,492

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the radicalness of the subsequently created level-one and level-two patents. *Pledge-related patent* includes level-one patents in column (1) and level-two patents in column (2). The variables are described in Table 1. Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 19: Relatedness to the pledged patents and the probability of being traded

VARIABLES	(1) Traded patent	(2) Traded patent by non-IBM
Pledge-related patent	0.068***	0.067***
	(0.002)	(0.002)
Openness	-5.96e-05***	-6.02e-05***
	(1.20e-06)	(1.20e-06)
Patent standardized forward citations	0.029***	0.023***
	(0.004)	(0.004)
Constant	0.265***	0.265***
	(0.002)	(0.002)
Year FE	YES	YES
Observations	979,729	979,729
Number of patents	170,924	170,924

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the probability of the patent being traded. *Pledge-related patent* is made equal to zero for all the years before 2005. The variables are described in Table 1. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 20: Outbound openness and market structure characteristics, the confounding effect of OIN

VARIABLES	(1) Total assignees Class	(2) Total assignees Class	(3) New-to-the-field entrants Class	(4) New-to-the-field entrants Class	(5) New-to-the-field entrants Class (%)	(6) New-to-the-field entrants Class (%)
Openness		2.446***		1.480***		0.002***
		(0.039)		(0.018)		(0.000)
OIN Openness	0.308***	-0.672***	0.165***	-0.431***	0.000***	-0.001***
	(0.045)	(0.022)	(0.022)	(0.010)	(0.000)	(0.000)
Openness x After 2005	8.456	4.616	-28.649***	-30.703***	-0.106***	-0.105***
	(8.901)	(8.704)	(4.055)	(4.076)	(0.009)	(0.009)
OIN openness x After 2005	0.087	-0.001	-0.003	-0.051***	-0.000***	-0.000**
	(0.053)	(0.041)	(0.026)	(0.018)	(0.000)	(0.000)
Constant	173.899***	175.720***	95.823***	96.797***	0.505***	0.504***
	(5.764)	(5.684)	(2.349)	(2.301)	(0.007)	(0.007)
Year FE	YES	YES	YES	YES	YES	YES
Observations	2,066	2,066	2,066	2,066	2,066	2,066
Number of tech classes	177	177	177	177	177	177

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the total number of participants, new-to-the-field entrants, and the percentage of new-to-the-field entrants out of the total number of participants in the technological classes, controlling for the effect of the launch of OIN. *OIN openness* is the claims-weighted patent count at the class level of OIN American patents in each technological class. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 21: Outbound openness and inventive volume, type, and markets for technology, the confounding effect of OIN

VARIABLES	(1) Total patents Class	(2) Total patents Class	(3) Radical patents Class	(4) Radical patents Class	(5) Total Trading Class	(6) Total Trading Class
Openness		4.715***		0.452***		-0.269
		(0.228)		(0.019)		(0.175)
OIN Openness	1.127***	-0.614***	0.104***	-0.065***	-0.196	-0.078
	(0.261)	(0.115)	(0.022)	(0.010)	(0.130)	(0.084)
Openness x After 2005	78.617*	56.447	1.383	-0.547	544.931***	544.370***
	(44.079)	(42.179)	(3.512)	(3.366)	(73.889)	(73.820)
OIN openness x After 2005	0.584*	0.078	0.045*	0.001	0.702***	0.689***
	(0.308)	(0.231)	(0.026)	(0.020)	(0.152)	(0.168)
Constant	427.509***	437.973***	38.518***	39.433***	137.212***	137.478***
	(27.327)	(26.481)	(2.308)	(2.234)	(25.045)	(25.032)
Year FE	YES	YES	YES	YES	YES	YES
Observations	2,066	2,066	2,066	2,066	2,066	2,066
Number of tech classes	177	177	177	177	177	177

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 on the total number of patents, radical patents, and traded patents in the technological classes, controlling for the effect of the launch of OIN. *OIN openness* is the claims-weighted patent count at the class level of OIN American patents in each technological class. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

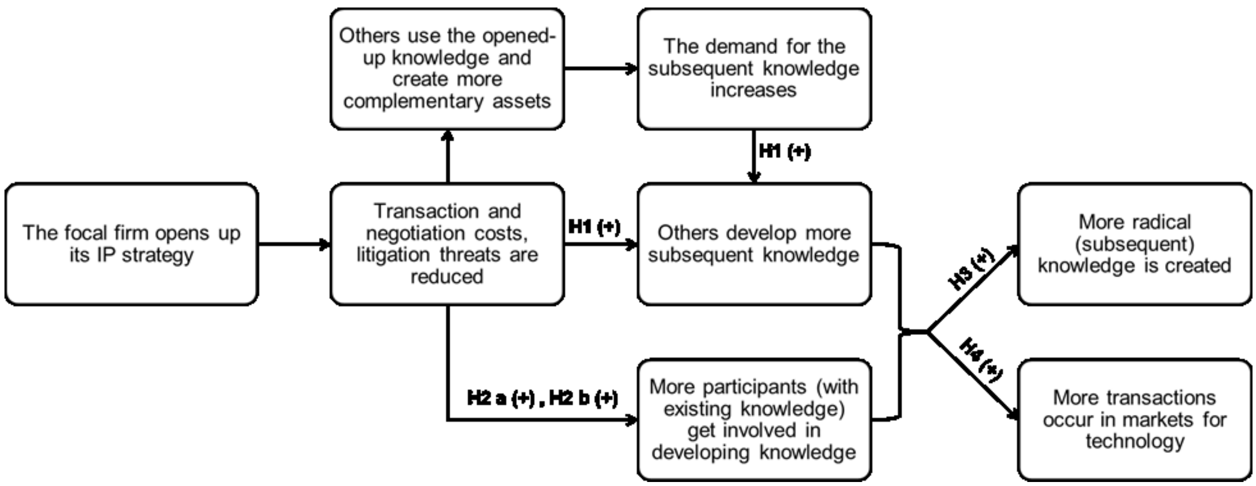
Table 22: Outbound openness and its effect over time

VARIABLES	(1) Total assignees $_{Class}$	(2) New-to-the-field entrants $_{Class}$	(3) New-to-the-field entrants $_{Class}$ (%)	(4) Total patents $_{Class}$	(5) Radical patents $_{Class}$	(6) Total Trading $_{Class}$
Openness	0.844***	0.369***	0.000	3.449***	0.306***	0.644***
	(0.024)	(0.016)	(0.000)	(0.142)	(0.013)	(0.122)
Openness x Years 2006&2007	0.103***	0.041**	-0.000*	0.618***	0.054***	0.241**
	(0.026)	(0.020)	(0.000)	(0.151)	(0.014)	(0.104)
Openness x Years 2008&2009	0.116***	0.034	-0.000***	0.744***	0.059***	0.511***
	(0.039)	(0.026)	(0.000)	(0.219)	(0.020)	(0.163)
Openness x Year 2010	0.121***	0.017	-0.000***	0.645**	0.049**	0.708**
	(0.043)	(0.025)	(0.000)	(0.251)	(0.024)	(0.293)
Constant	175.085***	96.930***	0.505***	433.090***	39.041***	132.671***
	(5.654)	(2.275)	(0.007)	(26.382)	(2.218)	(25.910)
Year FE	YES	YES	YES	YES	YES	YES
Observations	2,066	2,066	2,066	2,066	2,066	2,066
Number of tech classes	177	177	177	177	177	177

Note: This table reports the results from linear regressions of the effect of outbound openness after 2005 in smaller time periods on all the variables of interest at the level of the technological class. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

2.8 FIGURES

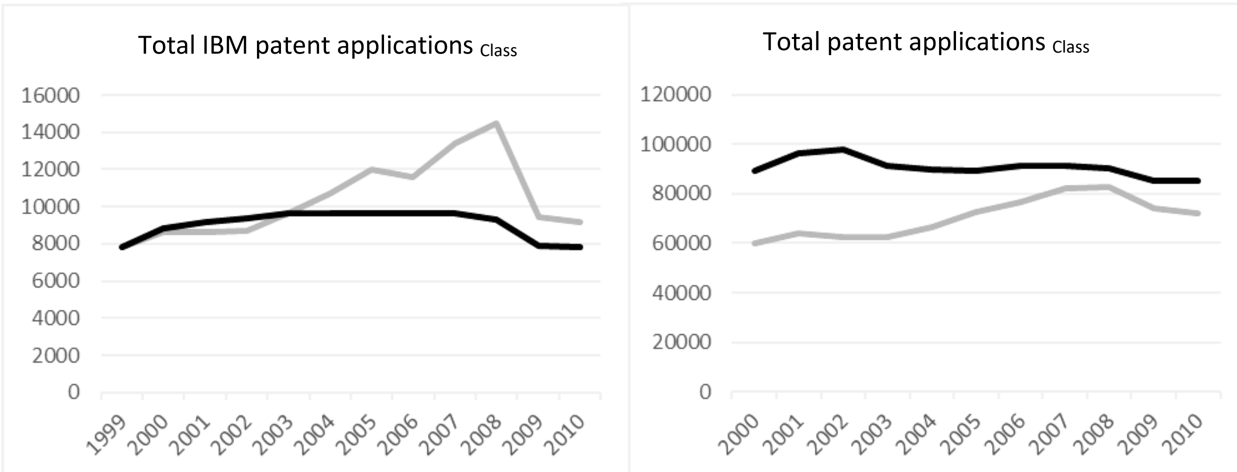
Figure 1: Outbound openness and the subsequent innovation process



Note: This figure[38] depicts the implications of outbound openness on the innovation amount and type, market structure characteristics, and trading activities in markets for technology, as discussed in the section Theory and Hypotheses.

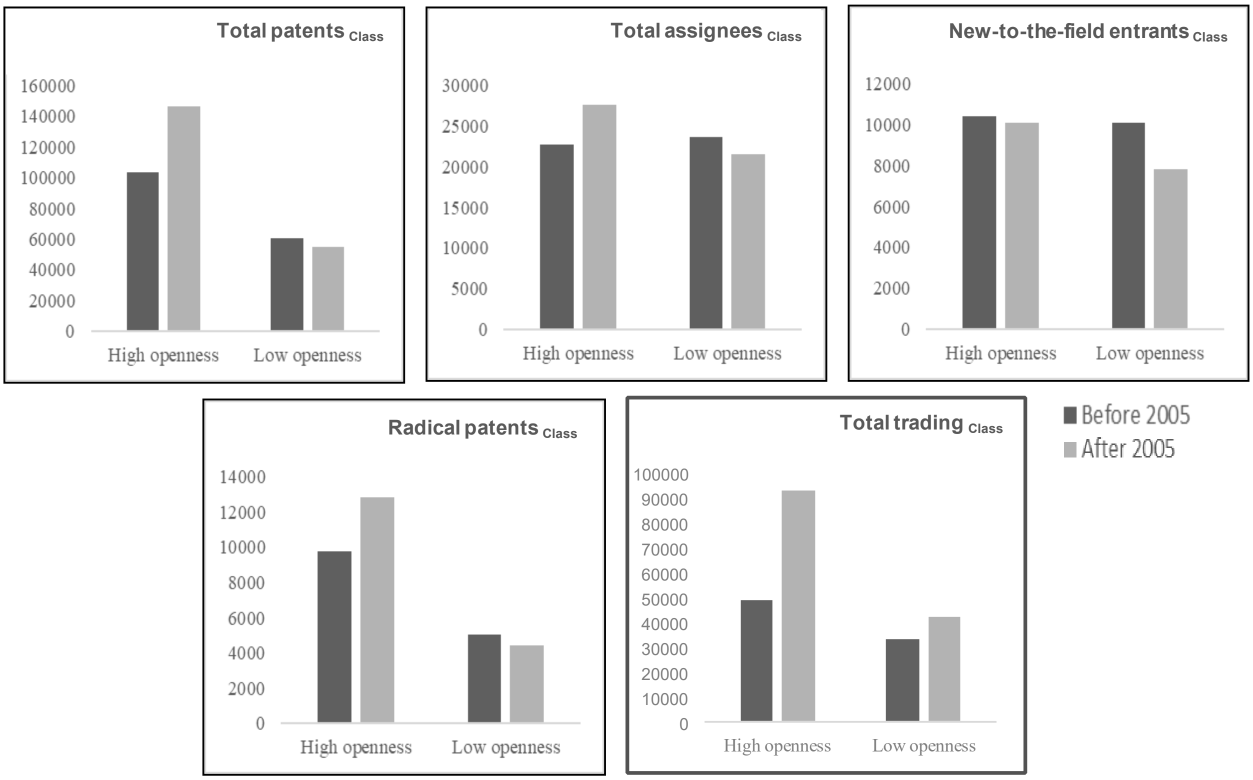
[38] This figure is adapted from Figure 1 in Ayvazyan, Matr (2019, p. 47) that illustrates the implications of outbound openness for the focal firm.

Figure 2: Total patent applications by IBM and total patent applications by all the firms in treated vs control technological classes



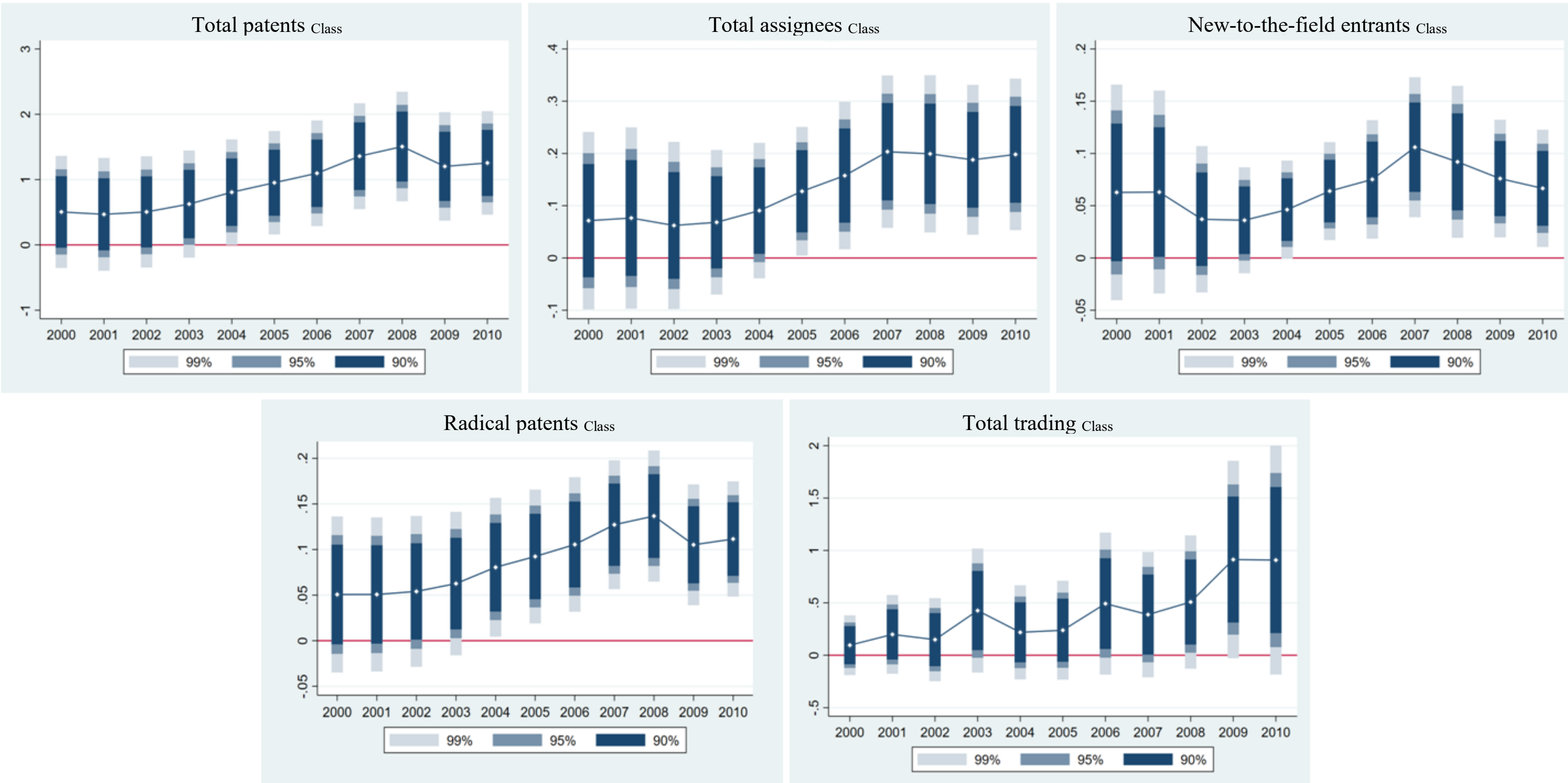
Note: This figure depicts the evolution of the number of patent applications made by IBM and the number of patent applications made by all the firms in the treated and control technological classes. The series with the dark line represents the control group, while the one with the light gray line represents the treated group of classes.

Figure 3: Average number of total patents, assignees, new-to-the-field entrants and trading in markets for technology in high and low technological classes before and after the pledge



Note: This figure depicts the average *Total patents $_{Class}$*, *Total assignees $_{Class}$*, *New-to-the-field entrants $_{Class}$*, *Radical patents $_{Class}$*, *Total trading $_{Class}$*, for technological classes with high versus low levels of openness before and after 2005. *High openness (Low openness)* refers to the first (last) ten technological classes, according to their openness measure. *Before 2005* includes the period between 1999 and 2004, while *After 2005* includes the period from 2005 to 2010.

Figure 4: Outbound openness and inventive volume, market structure characteristics, inventive type, and markets for technology



Note: This figure depicts the effect of outbound openness on *Total patents* $_{Class}$, *Total assignees* $_{Class}$, *New-to-the-field entrants* $_{Class}$, *Radical patents* $_{Class}$, *Total trading* $_{Class}$ over time.

Chapter 3

Board Independence and Acquisitions of External Knowledge: Overcoming the NIH Syndrome

3.1 INTRODUCTION

While the benefits of incorporating outside knowledge into firm's innovative trajectories[39] have been well acknowledged among both academics (Teece, 2006; Chesbrough, 2003; Cassiman & Veugelers, 2006, Laursen & Salter, 2006; Arora & Gambardella, 2010) and practitioners (Huston & Sakkab, 2006), examples of organizations' resisting externally developed[40] ideas and inputs are plenty. In the early 1990's, Apple Inc.'s managers, being skeptical about the ideas stemming from external sources (Burrows & Greene, 2000), stubbornly rejected implementing a two-button, instead of a one-button computer mouse design, long after the feedback from the market and the conducted usability research revealed that mouse devices should optimally have two buttons (Lidwell, Holden, & Butler, 2010). Another practice is Philip's redesigning and reengineering the already famous Sonicare power-toothbrush (Lidwell et al., 2010), after its acquisition of Optiva Corporation, the producer of that toothbrush, in 2000.

This bias against external knowledge and innovations, labeled as the "Not Invented Here" (NIH) syndrome is present in many organizations (Antons & Piller, 2015) and may ultimately result in suboptimal performance and superfluous effort in creating duplicative innovations (Katz & Allen, 1982; Allen et al., 1988). Though it is particularly well documented in the prior literature at the level of R&D workers and teams (Katz & Allen, 1982; Kathoefer & Leker, 2012; de Araújo Burcharth, Knundsen, & Søndergaard, 2014), it can also span across all the other organizational levels, including the R&D managers and CEOs. Accordingly, the NIH syndrome may induce organizations to reject potentially valuable pieces of external knowledge

[39] Benefits from the external knowledge acquisition have been discussed in the prior literature. Among other benefits, they can facilitate a) avoidance of having duplicative innovations, b) a faster and arguably less uncertain way to obtain the innovative outcomes in comparison to internal R&D solutions, c) a better fit for innovations and the firms and d) a specialization of innovative labor (Arora & Gambardella, 2010).

[40] The externality can have different levels: spatial, organizational, and hierarchical (Antons & Piller, 2015). In this paper, by externally developed knowledge, we refer to the knowledge originated from an outside entity.

(Agrawal, Cockburn & Rosell, 2010; Hussinger & Wastyn, 2016), leading to a slower and less efficient development of technological solutions. Thus, given the complexity of the process of the absorption of external knowledge - which should not be taken for granted (Cohen & Levinthal, 1990) - a question of interest arises: What mechanisms can help firms counteract such NIH behaviors?

In this paper, we test whether the independent directors on the board can help increase outside knowledge acquisitions and mitigate the problem of NIH in technology-intensive industries. This syndrome can be interpreted as an agency issue (Antons & Piller, 2015), where individuals (e.g. CEOs and R&D managers) may bear important personal costs in taking actions to change attitudes and thus end up acting opportunistically (Eisenhardt, 1989). Prior research has shown that greater board independence, which brings in increased monitoring on managers and advising, helps to solve the agency problem, primarily through its supervisory function. Besides, the structural independence of these directors suggests that their greater presence on the board leads to a better control of managerial decisions made on behalf of the firm's shareholders (Fama & Jensen, 1983). Since outside directors are not subordinate to (and therefore, their careers do not depend on) the CEOs, they are more likely to confront managerial decisions that can potentially put the interests of the shareholders at risk. Rather, these directors have the credibility to fire the CEOs after a poor performance (e.g. Williamson, 1983).

Recent research has shown that due to their monitoring role, independent directors influence the amount and type of the innovations internally developed by companies (Balsmeier, Fleming, & Manso, 2017). The authors primarily draw on career concerns perspective when interpreting the findings of increased innovative output delivered by firms and enhanced performance along known innovative trajectories. They explain that managers become more risk-averse and more inclined to put managerial effort to yield innovative outputs, due to increased board independence. In this paper, we examine if independent directors can operate as a mechanism to overcome the NIH syndrome and spur the acquisition of external knowledge. An important element in our theoretical arguments is that the strengthened monitoring and advice from these directors will push managers to recognize opportunities and exploit outside knowledge through markets for technology. Thus, we hypothesize and empirically demonstrate that a higher presence of independent directors is associated with a higher probability of acquiring outside knowledge. A complementary difference-in-difference analysis using the passage of Sarbanes-Oxley act (SOX) in the U.S. in 2002 as an exogenous shock in the presence of independent members in boards of directors (Faleye, Hoitash, & Hoitash, 2011; Balsmeier et al., 2017) suggests that the relationship is likely to be causal. Furthermore, we provide evidence indicating that the positive impact of independent directors on the acquisition of external knowledge is stronger for companies with more stable R&D teams, where the NIH syndrome is more likely to be present. Finally, our results also indicate that the impact of independent directors is less intense in corporate contexts where the CEO has more power, suggesting that the process is driven by the monitoring role of independent directors rather than their advisory role. Overall, the evidence provided by this collection of findings suggests that the presence of independent directors in corporate boards favors the incorporation of external knowledge by inducing managers to take actions to overcome the NIH syndrome.

Our study makes a contribution to the field of organizational strategy by connecting the consequences of actions at the corporate governance level to organizational outcomes that are to a large extent driven by individual and group processes. Past research on potential remedies to the NIH syndrome has pointed at the structure of intra-organizational communication patterns and the incentive system (Merwald, 1999; Pay, 1995; as cited in Antons & Piller, 2015). Our results suggest that any action in these (or other) aspects of organizational structure aimed at reducing resistance against external knowledge may impose personal costs on managers and, thus, needs to be encouraged at the highest corporate level. Our results also contribute to the corporate governance literature on the role of independent members of boards of directors. Independent directors are typically seen as providers of counsel and oversight to top managers. Our evidence indicates that their impact on external acquisitions of knowledge diminishes with the position of the power of the CEO. While this result does not necessarily neglect the advisory role of independent directors, it underlines the relevance of their monitoring function. Finally, we also contribute to the line of literature on the factors that lead to under-investing in external technology acquisitions (see Arora & Gambardella, 2010). This research, compared to other factors like firm's capacity to identify and assimilate external knowledge flows (see, e.g., Volberda, Foss, & Lyles, 2010; Zou, Ertug, & George, 2018), has paid relatively less attention to the role of the attitudes of the members of the organization towards external pieces of knowledge.

3.2 THEORY AND HYPOTHESES

To derive theoretical predictions on the effect of board independence on firm's engagement in acquisitions of external knowledge, we draw from different strands of literature. We begin this section by analyzing prior research to argue that independent directors can affect the firm's decision to acquire external knowledge. Next, we hypothesize how this impact might be moderated in contexts where NIH is especially relevant. Finally, we investigate the moderating effect in contexts where the board's monitoring function is mitigated.

3.2.1 Independent Directors and the Acquisition of External knowledge

Extant literature has analyzed the role of independent members of corporate boards of directors (see Adams, Hermalin, & Weisbach, 2010, for a review). While internal members of the board of directors may be subject to (implicit or explicit) conflicts of interest that generate loyalty to the CEO (Pfeffer, 1981), outside directors' incentives are expected to be better aligned with shareholders' interests (Rosenstein & Wyatt, 1990; Byrd & Hickman, 1992, Duchin, Matsusaka & Ozbas, 2010). Because their actions are driven by their reputation as directors (Masulis & Mobbs, 2014), their presence in corporate boards contributes to a more intense monitoring and advising of company managers (Faleye et al., 2011).

The oversight and advice of independent directors, however, does not necessarily lead to better strategic decisions. To the extent that independent directors may have less firm-specific information than insiders, they may decrease the value of decision-making. Accordingly, research has found that while independent members contribute to intensifying the supervisory function of boards, the impact of this increased monitoring on shareholder value will depend on the complexity of corporate activities (Duchin et al., 2010; Faleye et al., 2011). In terms of innovation policy, Balsmeier et al. (2017) identify a shift towards more patent-intensive and familiar technologies in firms whose board of directors transitioned from a non-independent to an independent majority. This evidence suggests that an increase in the presence of independent directors in corporate boards induces managers to focus on more tangible indicators of R&D performance.

In terms of the balance between the use of internal and external sources of knowledge, past research has documented a clear tendency by individuals to oppose against ideas and technologies that are considered to come from the outside, with negative consequences for the long-term innovation performance of their organizations. This NIH syndrome (Clagett, 1967) takes place at the group level (Katz & Allen, 1982), but also at the organizational level (Agrawal et al., 2010, Hussinger & Wastyn, 2016). The NIH syndrome in innovation activities may be the result of rational R&D workers trying to avoid adding a new burden to their workload or implicitly disclosing negative information on the value of their past output (Antons & Piller, 2015). It can also arise, however, from biases in the evaluation of technological alternatives, such as the confirmation bias that leads people to cherry-pick information consistent with their initial prior assessments (Nickerson 1998), or in-group favoritism spurred by the defense of an organizational identity leading to suboptimal technical decisions (Hussinger & Wastyn, 2016).

Independently of its individual or social roots, the NIH syndrome has traditionally been seen by the academic literature and managerial practice as an important obstacle to the creation of value, closely associated with organizational inertia (Antons & Piller, 2015). Individuals and groups in the R&D function of firms are expected to show resistance to change, especially when it involves incorporating outside knowledge. Managers may also suffer from the NIH syndrome at the organizational level. Even if they do not, they will find it particularly costly to implement projects that involve integrating outside pieces of knowledge and will therefore tend to discard them. Thus, the NIH syndrome can be viewed as an agency problem at the corporate level, and a higher presence of independent directors in the corporate board will contribute to overcoming this tendency. First of all, the supervisory function of independent directors is expected to attenuate the agency problem in the firm's governance in general. Independent directors tend to promote more incentive-based pay (Knyazeva, Knyazeva & Masulis, 2013). This may induce managers to bear the personal costs of making an unpopular R&D decision that they would have otherwise avoided. Second, the high level of awareness among management practitioners of the existence of NIH syndrome as an obstacle for performance makes it particularly likely that actions to overcome it are advised and rewarded by independent directors. Even if as company outsiders, they may have more inferior information than inside directors for their general strategic advisory role, they are also expected to suffer less from biases against external knowledge sources. This is due to their relative isolation from other members of the organization, and their increased contact with members from other organizations. Thus, independent directors are expected to provide a less internally biased assessment in their evaluation of the technological opportunities faced by the company. In conclusion, we expect a higher presence of independent directors in corporate boards to lead to an increase in acquisitions of knowledge from other organizations.

Hypothesis 1: A higher presence of independent members in a firm's board of directors will lead to an increase in acquisitions of external knowledge.

3.2.2 Research Workforce Stability

Existing research on the NIH syndrome at the micro level suggests that the process is accentuated by project tenure in research groups (Katz & Allen, 1982). Similarly, opposition to external knowledge at the organizational level is also related to the stability of its research workforce. One of the key drivers of the NIH syndrome at the organizational level is the existence of in-group favoritism, and the corresponding out-group derogation, as mechanisms that reinforce group affiliation and social identity (Agrawal et al., 2010; Hussinger & Wastyn, 2016). Actions that strengthen social identity pay group members back in terms of higher self-esteem and trust, which facilitates intra-group transactions (Efferson, Lalive, & Fehr, 2008). Furthermore, the prospect of future repeated interactions among group members induces the development of group affiliation and social identity (Lembke & Wilson, 1998). Consequently, these processes are favored by a stable group composition. A stable workforce in the organization will tend to generate a strong social identity and therefore a strong opposition against external contributions. Moreover, a stable *research* workforce will lead to a particularly intense NIH syndrome, since researchers are especially concerned by the incorporation of new technological knowledge. As the resistance against external knowledge is linked to the NIH syndrome, this will become a setting, where the need for external knowledge is even larger. In consequence, corporate governance mechanisms that contribute to alleviating the NIH syndrome will have a stronger impact in the context of a stable research workforce, where such syndrome is particularly likely to be present.

Hypothesis 2: A higher presence of independent members in a firm's board of directors will lead to a stronger increase in acquisitions of external knowledge in companies with a more stable research workforce.

3.2.3 Stability of Researcher Collaborations

Past research has also underlined the role of work routines and protocols as antecedents of the NIH syndrome (Clagett, 1967; Katz & Allen, 1982; Kathoefer & Leker, 2012). These routines and protocols, which generate security among members of the organization, may be disturbed by the introduction of external knowledge (Kathoefer & Leker, 2012) and thus generate resistance against it. Protocols and routines naturally appear as a coordination mechanism among members of the organization that need to co-operate frequently. Even if managers centralize to some extent the implementation of procedures in order to regulate the interaction between the firm's members, specific work routines will be more deeply developed when members tend to collaborate repeatedly with the same co-workers. In particular, researchers that frequently team up with the same group of co-inventors in their innovation activities are expected to establish well-developed working routines and oppose to the introduction of external knowledge (Katz & Allen, 1982). Hence, the NIH syndrome is particularly likely to be present in organizations with stable collaborations among researchers, which makes the "objective" need for external knowledge particularly relevant. Therefore, we expect that corporate governance mechanisms that counteract this syndrome will be particularly useful in this context.

Hypothesis 3: A higher presence of independent members in a firm's board of directors will lead to a stronger increase in acquisitions of external knowledge in companies with more stable inventor collaborations.

3.2.4 Board Monitoring as an Underlying Channel

CEO duality is frequently viewed as an impediment to the board's monitoring of top executives (Jensen, 1993; Aguilera, 2005) and can serve to entrench a CEO within an organization by compromising the board's abilities to monitor and discipline management (Mallette & Fowler, 1992; Tuggle et al., 2010). In addition, Jensen (1993) states that CEOs almost always set the agenda and control the information given to the board, which can hinder the ability of board members to contribute effectively to the monitoring and evaluation of the CEOs. Empirically, Tuggle et al. (2010) show that CEO-Chairs can steer boards' attention away from monitoring issues towards topics that suit their own interests, by setting and implementing more detailed, rigid agendas. To the extent that managers suffer from the NIH syndrome, a powerful CEO may limit the power of the board to monitor such decisions, by managing the information flow and setting the agenda away from topics related to buying technology in the market. Taking these arguments together, we hypothesize that:

Hypothesis 4. A higher presence of independent members in a firm's board of directors will lead to a lower increase in acquisitions of external knowledge in companies with CEO duality.

In addition to having a direct influence on the board monitoring ability, managers may use the protection granted by anti-takeover provisions to allocate firm resources for their personal benefit (Shleifer & Vishny, 1989). This view, sometimes called "managerial welfare hypothesis" (Mahoney, Sundaramurthy, & Mahoney, 1997), has received substantial empirical support in the literature (see Straska & Waller, 2014). As first stressed by Manne (1965), such insulation might harm shareholders by weakening the disciplinary threat of removal and thereby increasing shirking, empire-building, and extraction of private benefits by incumbents. While some provisions, such as golden parachutes, may increase the cost (and threat) of CEO dismissal and as a result reduce the power of the board to take disciplinary actions, anti-takeover provisions may also impact the incentives of directors to engage in monitoring. Independent directors are usually powerful individuals, present or former CEOs, or top professionals with a reputation at stake (Deutsch, Keil, & Laamanen, 2011). When the market for corporate control becomes active, it serves as evidence of the failure of other governance mechanisms (Dalton et al., 2007). To protect their reputation as effective monitors, independent directors may have additional incentives to exert influence and steer managers towards firm value when there is a credible threat that poor management (and ineffective monitoring) will trigger a takeover reaction. As a result, we expect the positive effect of board independence to be stronger in the absence of anti-takeover mechanisms.

Hypothesis 5: A higher presence of independent members in a firm's board of directors will lead to a lower increase in acquisitions of external knowledge in companies with anti-takeover provisions.

3.3 DATA AND METHODS

3.3.1 Data

To test our hypotheses, we draw on data from several sources. Information on boards of directors is taken from the Investor Responsibility Research Center (IRRC) database that has been widely used in the literature on board independence (e.g. Duchin et al., 2010; Balsmeier et al., 2017, etc.). Among other items, it classifies each director of an S&P 1500 firm into an employee, independent, or linked-affiliated (e.g. former employee, relative of an executive director, provider of legal, consulting or financial services to the firm, firm's customer or supplier, etc.) board member. We complement board of directors' information with firm-level financial data, such as sales, R&D expenditures or number of employees from Compustat. For patent data, we rely on Arora, Belenzon, & Sheer (2019) that largely extends and improves the historical NBER patent dataset (Hall, Jaffe, & Trajtenberg, 2001; Bessen, 2009). This dataset includes the number of (granted) patents per firm-year and provides a firm identifier allowing us to connect the patent-related data with Compustat and IRRC. Finally, we obtain external knowledge acquisition data from the USPTO Patent Assignment Dataset (PAD), which identifies changes of ownership in the U.S. patents. One advantage of using these data instead of licensing or alliance transactions is that most patent ownership transfers are filed with the USPTO, since only by recording patent (re)assignments with the database, parties can provide evidence of ownership transfer in courts[41]. For each recorded patent transaction, the dataset includes the execution (recording) date, the patent(s)/patent application(s) involved, the names of the assignee and the assignor, and the transaction type (e.g. assignment, merger, government, name change, etc.). We mainly consider inter-firm assignments of patents and thus disregard inventor-to-employer transfer of rights, transactions due to name changes, name corrections, government interest or securities.

Our sample initially comprises a panel of public U.S. firms that were included in the IRRC database for the period 1996-2010, with their corresponding records on board structure, patents, patent transactions and financial information. After excluding firms from highly regulated sectors and financial industries (SIC codes 4000-4999 and 6000-6999), as well as firms that do not heavily invest in R&D[42], we are left with 1716 unique firms and 11711 firm-year observations. The final sample size varies across different analyses, according to data availability for the different variables.

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[41] Despite the fact that from a legal perspective, for a patent (re)assignment to be considered as legally binding parties have to record it with the USPTO, doing it is not legally mandatory. Therefore, while it cannot be taken for granted that data from the PAD accurately represents the population of patent transfers (Marco et al., 2015), firms do have incentives to record their patent assignments with the USPTO. As Serrano (2010) notes, “anecdotal evidence from interviews with patent lawyers strongly supports the effective recordation of transfer of patents”.

[42] We consider a firm as “heavily investing in R&D,” according to whether or not the R&D spending of the firm is more than the industry (according to SIC codes) median.

3.3.2 Empirical Model

To test how board independence affects firms' subsequent engagement in acquisitions of knowledge from the outside, we estimate the probability that a firm buys at least one patent in t+1, using the following linear probability model:

$$\boldsymbol{P_{it}(Y_{i,t+1} = 1) = \beta_0 + \beta_1 Ind\ dir\ \%_{it} + \gamma\, Z_{it} + \delta_i + \theta_t + \mathcal{E}_{it}},$$

where *i* indexes firm and *t* indexes year. The dependent variable, $Y_{i,t+1}$, is a binary indicator equal to one, if a firm buys at least one patent in *t+1*. The main variable of interest, *Ind dir %*, is the share of independent directors on the board of the firm *i* in year *t+1*. The vector Z_{it} is comprised of time-varying factors used as control variables in the analysis (see Appendix). Firm fixed effects are captured by δ_i to account for unobserved time-invariant firm-level heterogeneity, and θ_t are year fixed effects. We use a linear probability model and cluster standard errors at the firm level.

Addressing Endogeneity. Due to potential endogeneity concerns about board structure (Hermalin & Weisbach, 1998; Adams et al., 2010), a causal claim may not be made from the simple OLS estimations, with *Buying probability* as dependent and *Ind dir %* as independent variables. Board composition reflects a firm choice, which may be correlated with some observable, as well as unobservable firm characteristics that also influence the probability of engaging in external knowledge acquisitions. Another potential concern is that these variables may be jointly determined. On the one hand, enhanced monitoring from the independent directors can increase the likelihood of buying outside knowledge. On the other hand, external knowledge acquisitions might attract more independent directors to join the firm's board. While the fixed effects in our main empirical model partially address the omitted variable bias, it does not necessarily address the possibility of reverse causality. Thus, to obtain a more consistent estimate of the board composition on external knowledge acquisitions, we follow prior studies (e.g. Duchin et al., 2010; Balsmeier et al., 2017; Lu & Wang, 2018) that have largely used the regulatory changes requiring public firms to increase their share of independent directors on the boards, in order to account for exogenous variations in the share of independent directors.

In particular, we make use of the passage of Sarbanes-Oxley Act (SOX) in 2002 following the Enron corporate scandal (and the subsequent regulatory changes by NYSE and Nasdaq in 2003 with stricter requirements) to complement our main analyses with a differences-in-differences approach[43]. The main requirement from the regulation was to have a majority of independent directors on the board (and a 100% audit committee). Figure 1[44] provides the evolution of board independence over the sampling period 1996-2010 and illustrates a substantial increase in the presence of independent directors after 2001. It also shows that from around 63% in 1996, the percentage of independent boards increased to about 98% by 2010.

Insert Figure 1 about here.

Following existing research, we identify the treated firms as non-compliant, i.e. firms that had a minority of independent directors, and the control firms as compliant, i.e. firms that had a majority of independent directors and a 100% independent audit committee prior to the regulations. Next, we track the point in time when the treated firms switched to a majority board independence and had a fully independent audit committee in 2001 or later. Figure 2 provides a graphical illustration of the average *Buying probability* among the treated and control groups of firms over time. Meanwhile, our regression analyses estimate the following model:

$$\boldsymbol{P_{it}\left(Y_{i,t+1} = 1\right) = \beta_0 + \beta_1 Treated_i x\ After\_treat_t + \gamma\, Z_{it} + \delta_i + \theta_t + \mathcal{E}_{it},}$$

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[43] For a detailed description of the identification strategy, see e.g. Balsmeier et al. (2017).

[44] Similar to data from Figure 1 from Balsmeier et al. (2017, p. 539).

where all the notations remain the same, except from the main term of interest, *$Treated_i$ x $After\_treat_t$*, which captures the extra effect of the switch from a minority to a majority board independence.

Insert Figure 2 about here.

3.3.3 Dependent Variable

Acquisition of external knowledge (Buying probability). This variable is a dummy indicator that tags whether the firm acquires at least one patent from another firm[45] in a given year, drawing on data from PAD. A major challenge of using these data for firm-level analyses is that the recorded names of the assignees (buyers) and assignors (sellers) have never been standardized. Thus, prior to matching PAD with IRRC-Compustat firms, we conduct a name standardization procedure (Bessen, 2009; Arora et al., 2019) for the assignee names in both databases, in order to decrease the possibilities of spelling inconsistencies (see Appendix 1 that provides a detailed description of the steps performed). We also perform some supplementary manual checks to account for changes in the names of the firms in our sample, and then fuzzy-match them with the standardized assignee names from PAD.

3.3.4 Main Independent Variable

Percentage of Independent Directors in the Board (Ind dir %). Using information on whether the director is independent or not, as provided in the IRRC Director database, our main independent variable indicates the ratio between the total number of independent directors on the board and the total number of directors on the board.

[45] As noted above, we eliminate the transaction from inventors to the focal firm, transactions that are filed due to due to name changes, differences, or corrections, due to government interest or securities. Appendix 1 discusses the steps for this variable's construction.

3.3.5 Moderators Related to the Intensity of the NIH Syndrome

Research workforce stability. This variable is constructed following the steps below. First, for each firm, we identify its current inventors (patenting in *t*) using USPTO identifiers (Monath & McCallum, 2015). For each of these inventors, we create a dummy indicating whether she filed with the firm in *t-1* or/and in *t-2*. We then aggregate these values at the firm-year level, which allows us to obtain the number of inventors in *t* that also filed patents with the focal firm at *t-1* or/and in *t-2*. Finally, we define *Research workforce stability*, via dividing this number by the total number of inventors patenting in *t*. The logic behind this measure is that a higher proportion of inventors with patents in both one/two years prior and *t* indicates a higher stability of the inventor workforce.

Inventor interactions stability. For this measure, first, at the inventor-year level, we count the number of co-inventors each of the inventors of the firm has in *t*. Second, for each of the focal inventors, we track those co-inventors (from step one) with whom she patented in *t-1* or/and *t-2*. We then take the ratio between the number of "old" co-inventors (from step 2, with previous patenting history) and the total number of current co-inventors. Finally, we aggregate these values at the firm-year level, by taking the average. We thus define *Inventor interactions stability* as the average proportion of prior inventor interactions.

Inventor team stability. To create this variable, first, we start by identifying every exact combination of co-inventors in a patent application as a distinct team. For each patent, we verify whether the team of inventors patented together in *t-1* or/and *t-2*. We then aggregate these values at the firm-year level, creating an indicator of the number of patenting teams that have obtained patents with the focal firm in the previous two years. In the final step, we take its ratio with the total number of teams patenting in *t* and define *Inventor team stability* at the firm-level.

3.3.6 Moderators Related to the Power of the CEO

The two indicators we use for CEO power are a) *CEO duality*, which is a dummy variable equal to one if the CEO of the firm also acts as the Chairman of the board, and b) *EINDEX* (i.e. Entrenchment Index), which counts the number of the corporate governance provisions in place, following the method from Bebchuk, Cohen, & Ferrell (2009). In particular, we compute how many of the following measures are in place: golden parachutes, poison pills, classified boards, supermajority votes, limited charter amendments, and limited bylaws amendment. All these provisions "protect" the managers from getting fired. Therefore, higher (lower) levels of *EINDEX* indicate that the managers are less (more) likely to be subject to career concerns and takeover pressures.

3.3.7 Controls

We control for *Ln(Employees)* to allow for a comparison of firms of similar size. We also include *Ln(R&D/assets)*, to account for the intensity of the innovation input, R&D; as well as *Ln(Patents)*, to account for the innovation output. Other control variables are *Ln(Cash/assets)*, *Ln(Sale)*, *Ln(Firm age)*, and *Leverage*. Appendix 2 describes all the variables used in different analyses.

3.4 RESULTS

3.4.1 Descriptive Results

Table 1 provides summary statistics of the main variables used in this study. The firms in our sample are large: they employ on average more than 16800 workers, have around $6.8 million in net sales and are granted about 44 patents. On average, firms in our sample have a board of directors comprised of 9 members, with around 67% independent directors. An average firm is 27 years old, has $593 millions in cash, and invests $192 millions in R&D. The correlation matrix from Table 2 does not seem to indicate alarming values for any of the correlations among the variables.

Insert Tables 1 and 2 about here.

3.4.2 Univariate Analysis

Panel A in Table 3 demonstrates a positive pair-wise correlation matrix between *Ind dir %* and *Buying probability*. Panel B can be interpreted in the following way: if greater levels of independent directors on the board are linked to a higher probability of IP acquisitions, the mean outcome measures should increase across quartiles. Computing the t-statistics of differences in means between the quartiles displays a quite consistent positive association between the share of independent directors and *Buying probability*.

Insert Table 3 about here.

Table 4 describes the main variable of interest, the share of independent directors on the board, according to four quartiles for our sample firms. In the first quartile, the average value of the board independence is below 50%, indicating non-independence of the boards, while in the next three quartiles, the boards are on average, independent.

Insert Table 4 about here.

3.4.3 Main Results

Columns (1) in Table 5 reports the results from the Linear Probability Model panel regressions of *Buying probability* on *Ind dir %* (Independent director share) with year and firm fixed effects. The findings suggest that there is a positive and significant association between board independence and the probability of acquiring external knowledge. A 10 percentage-point increase in the proportion of independent directors is expected to increase buying probability by 0.78 percentage points, which implies around 1.5% increase with respect to the average probability level. Column (2) reports the results from a difference-in-differences panel analysis, using the SOX regulatory changes, and confirms the results from Column (1), as seen from the interaction term *Treated* x *After_treat*. These findings support our Hypothesis 1.

Insert Table 5 about here.

Table 6 groups the results from interaction effects for Hypotheses 2 and 3. While we do not find enough evidence from Column (1) to support Hypothesis 2, the results from Columns (2) and (3) suggest that the effect of board independence on the buying probability is intensified when the firm has a more stable pattern of collaborations among inventors. For example, while the estimated impact of a 10 percentage-point increase in the share of independent directors on *Buying probability* is of 0.75 percentage points for companies with mean values of team stability, the expected effect increases to 1.58 percentage points for companies that double these average values. Altogether, we find partial support for the prediction that the effect of board independence is especially relevant in contexts where firms are more likely to suffer from the NIH syndrome.

Insert Table 6 about here.

Table 7 presents the findings from interaction effects that test Hypotheses 4 and 5 and suggests that the impact of board independence on buying probability is weakened when CEOs are more powerful, that is a) when the CEO is also the Chairman of the board, and b) with higher levels of the Entrenchment index. These results are in line with the intuition that when CEOs are more powerful, the independent directors' monitoring role is compromised. In particular, the results from the first column provide some support for Hypothesis 4, suggesting that the expected marginal effect on *Buying probability* of a 10 percentage-point increase in the share of independent directors decreases from 1.37 percentage points to a (non-significant) value of 0.44 percentage point. Likewise, the results shown in the second column offer support to Hypothesis 5. The estimated impact of independent directors decreases with the level of entrenchment of top managers. The estimated effect on *Buying probability* of a 10 percentage-point increase in the share of independent directors, ranges from 2.4 percentage points for companies with the lowest entrenchment levels to negative (non-significant) levels for companies with the highest levels of entrenchment.

Insert Table 7 about here.

3.5 CONCLUSIONS

Our paper sheds light on the relationship between board independence and the probability of engaging in buying transactions in markets for technology. Many firms are thought to underinvest in technology stemming from outside sources, inefficiently prioritizing the one created internally (Arora & Gambardella, 2010). This is despite the potential benefits (e.g. a faster and more efficient development of innovation, avoidance of duplicative innovations, etc.) that firms may obtain, by incorporating external knowledge and technology into their internal R&D processes. The mechanisms that may counteract this so-called NIH syndrome have not been paid substantial attention in the prior literature.

In this paper, adopting an agency perspective, we emphasize the role of the independent members of the board in overcoming the NIH-induced tendencies of rejecting external knowledge acquisitions. We explain that due to important personal costs, CEOs and R&D managers may be reluctant in taking actions for changing attitudes in favor of external knowledge incorporations and therefore, may engage in an opportunistic behavior, not in line with the interests of shareholders. Further, we argue that due to their supervisory function on managerial decisions, independent members of the board are likely to put pressure on CEOs to deliver the desired results. The main results from the Linear probability model, as well as the analysis, employing the passage of SOX regulations in the early 2000's, point at a positive effect of board independence on the buying probability in markets for technology. The aggregate findings from a set of tests for moderating effects, provide partial support for the intuition that the impact of independent directors is stronger in contexts in which the NIH syndrome is more likely to be present. In particular, the results suggest that the effect is intensified for firms with more stable inventor teams. Next, we also find that the effect is weakened in contexts where the CEOs are more powerful. Altogether, the propositions from our results can be summarized into two points: a) independent directors in corporate boards favor the incorporation of outside knowledge and help overcoming the NIH syndrome, and b) it is due to the monitoring role of the board of directors that their impact is particularly strong in contexts where (according to extant literature on NIH) more intense opposition (and more need for external knowledge) is expected.

Our study contributes to several streams of literature. First, linking corporate-level mechanisms with firm-level outcomes that are largely connected to individual- and group-level factors, we add to the organizational strategy research, by suggesting that corporate boards' involvement in reducing subjective resistance against outside technologies can be crucial. We also contribute to the corporate governance literature, by emphasizing the independent directors' monitoring function. Finally, our results add to the research on markets for technology studying the "demand for external technology", by providing a link between one of the factors driving underinvestment in the external technology acquisitions, namely, the existence of the NIH syndrome[46], with a potential remedy in the form of board independence.

[46] As Arora & Gambardella (2010) note, the other two possible answers are the absorptive capacity of the firms and the relationship between the internal and external R&D solutions.

3.6 TABLES

***Table 23*: Descriptive statistics of selected variables**

VARIABLES	Obs	Mean	Std.Dev.	Min	Max
Buying probability	11711	0.531	0.499	0	1
Ind dir %	11711	0.672	0.181	0	1
Research workforce stability	5131	0.396	0.220	0	1
Inventor interactions stability	4986	0.134	0.154	0	1
Inventor team stability	5131	0.262	0.197	0	1
CEO duality	10937	0.622	0.485	0	1
EINDEX	5553	2.686	1.407	0	6
Board size	11711	9.206	2.450	1	21
R&D	11711	191.940	713.427	0	12183
Patents	11711	44.666	191.828	0	5930.333
Employees (in thousands)	11588	26.243	73.919	0.002	2100
Sale	11701	6802.781	20444.690	0	425000
Firm age	11711	26.859	16.717	1	61
Cash	11695	593.400	1520.934	0.609	11155
Leverage	11642	0.225	0.179	0	1.678

Note: This table shows descriptive statistics of the main sample variables used in this analysis. The number of observations from control variables vary according to the test described in every table from here on. All variables are defined in Table A1 in Appendix 2.

***Table 24*: Correlation matrix**

	VARIABLES	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Buying probability	1.000														
2	Ind dir %	0.165	1.000													
3	Research workforce stability	0.079	0.072	1.000												
4	Inventor interactions stability	0.009	-0.034	0.602	1.000											
5	Inventor team stability	0.034	0.010	0.779	0.570	1.000										
6	CEO duality	0.051	0.094	-0.044	-0.029	-0.081	1.000									
7	EINDEX	0.036	0.331	0.006	-0.011	-0.008	0.031	1.000								
8	Board size	0.104	0.113	0.061	-0.016	0.013	0.109	0.075	1.000							
9	R&D/assets	0.311	0.034	0.002	0.023	0.048	-0.077	-0.052	-0.185	1.000						
10	Patents	0.214	0.106	0.152	0.023	0.109	0.042	-0.110	0.153	0.106	1.000					
11	Employees	-0.004	0.056	0.037	-0.035	-0.006	0.055	-0.088	0.295	-0.095	0.235	1.000				
12	Sale	0.096	0.111	0.057	-0.018	0.019	0.071	-0.108	0.309	-0.072	0.329	0.720	1.000			
13	Firm age	0.176	0.272	0.104	-0.012	0.029	0.176	0.092	0.471	-0.183	0.189	0.229	0.287	1.000		
14	Cash/ assets	0.156	0.032	0.047	0.032	0.073	-0.127	-0.043	-0.296	0.496	0.038	-0.127	-0.097	-0.264	1.000	
15	Leverage	-0.021	-0.036	0.001	0.017	0.002	0.082	0.005	0.175	-0.204	-0.018	0.088	0.042	0.127	-0.376	1.000

Note: This table reports the correlations among the main variables used in this analysis. All variables are defined in Table A1 in Appendix 2.

***Table 25*:** Correlation and univariate analysis of independent directors and acquisitions of external knowledge

Panel A: pairwise correlations	
	Buying probability
Ind dir % $_{t}$	0.165***
Ind dir % $_{t-1}$	0.174***

Panel B: univariate analysis				
Share of independent directors quartiles				
	Q1	Q2	Q3	Q4
Buying probability	0.423	.506^{+++}	0.600^{+++}	0.625^{+}

Note: Panel A reports the correlation between *Ind dir %* and *Buying probability*. Panel B reports the mean *Buying probability* for each quartile of firms based on the quartiles from the share of independent directors on the board. *** p<0.01, ** p<0.05, * p<0.1 for correlations. $^{+++}$ p<0.01, $^{++,}$ p<0.05, $^{+}$ p<0.1 for indicating whether the column's value is statistically different from the previous column's value.

***Table 26*:** Descriptive statistics for the share of independent directors on the board, based on quartiles

Quartiles	Obs	Mean	Std. Dev.	Min	Max
Q1	3324	0.438	0.124	0	0.571
Q2	3065	0.659	0.040	0.583	0.714
Q3	2619	0.775	0.028	0.722	0.818
Q4	2703	0.877	0.029	0.824	1

***Table 27*: Independent directors and acquisitions of external knowledge**

	(1)	(2)
VARIABLES	Buying probability	
Ind dir %	0.078**	
	(0.035)	
Treated x After_treat		0.054*
		(0.029)
Board size	0.006**	0.009**
	(0.003)	(0.004)
Ln (R&D/assets)	0.020	0.008
	(0.082)	(0.092)
Ln(Patents)	0.003	0.010
	(0.008)	(0.010)
Ln(Employees)	0.012	0.003
	(0.018)	(0.025)
Ln(Sale)	0.018	0.018
	(0.016)	(0.021)
Ln(Firm age)	-0.077*	-0.025
	(0.037)	(0.051)
Ln(Cash/assets)	-0.003	-0.053
	(0.062)	(0.084)
Leverage	-0.021	0.019
	(0.039)	(0.050)
Constant	0.416***	0.382**
	(0.131)	(0.166)
Observations	9,608	4,986
R-squared	0.724	0.722
Number of firms	1,434	1,434
Year FE	YES	YES
Firm FE	YES	YES

Note: Column (1) in this table presents the results from OLS panel regressions of the probability of engaging in buying in markets for technology on the share of independent directors on the board and a number of firm-level control variables. Column (2) in this table presents the results from a diff-in-diff panel regressions of the probability of engaging in buying in markets for technology on the interaction term between treated firms and the dummy *After_treat*. This interaction represents those firms that transitioned from a non-majority to a majority of independent boards in 2001 or later. Both columns include year and firm fixed effects. All the variables are described in Table A1 in Appendix 2. All the predictors are lagged by one year. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

***Table 28*: Independent directors and IP acquisitions: moderators related to the intensity of the NIH syndrome**

	(1)	(2)	(3)
VARIABLES		Buying probability	
Ind dir %	-0.016	0.011	-0.005
	(0.008)	(0.061)	(0.064)
Research workforce stability	-0.143		
	(0.118)		
Ind dir % x Research workforce stability	0.241		
	(0.158)		
Inventor interactions stability		-0.230	
		(0.151)	
Ind dir % x Inventor interactions stability		0.388*	
		(0.201)	
Inventor team stability			-0.270**
			(0.129)
Ind dir % x Inventor team stability			0.311*
			(0.174)
Constant	0.595***	0.631***	0.591***
	(0.191)	(0.194)	(0.190)
Observations	4,273	4,146	4,273
R-squared	0.500	0.497	0.501
Number of firms	654	636	654
CONTROLS	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES

Note: This table presents the results from OLS panel regressions of the probability of engaging in buying in markets for technology on the interactions of the share of independent directors on the board with moderators *Research workforce stability*, *Inventor interactions stability*, and *Inventor team stability*, and other firm-level control variables, as described in Table A1 in Appendix 2. All the predictors are lagged by one year. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

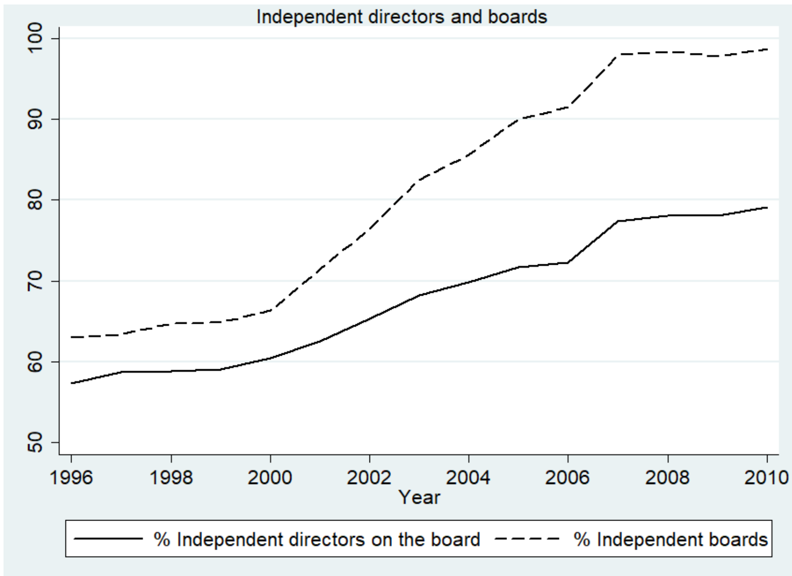
Table 29: Independent directors and IP acquisitions: moderators related to CEO power

VARIABLES	(1) Buying probability	(2) Buying probability
Ind dir %	0.137***	0.240***
	(0.048)	(0.077)
CEO duality	0.054	
	(0.037)	
Ind dir % x CEO duality	-0.093*	
	(0.052)	
EINDEX		0.045*
		(0.023)
Ind dir % x EINDEX		-0.059*
		(0.028)
Constant	0.471***	0.135
	(0.138)	(0.210)
Observations	9,208	4,460
R-squared	0.725	0.751
Number of firms	1,315	1,108
CONTROLS	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Note: This table presents the results from OLS panel regressions of the probability of engaging in buying in markets for technology on the interactions of the share of independent directors on the board with moderators *CEO duality* and *EINDEX*, and other firm-level control variables, as described in Table A1 in Appendix 2. All the predictors are lagged by one year. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

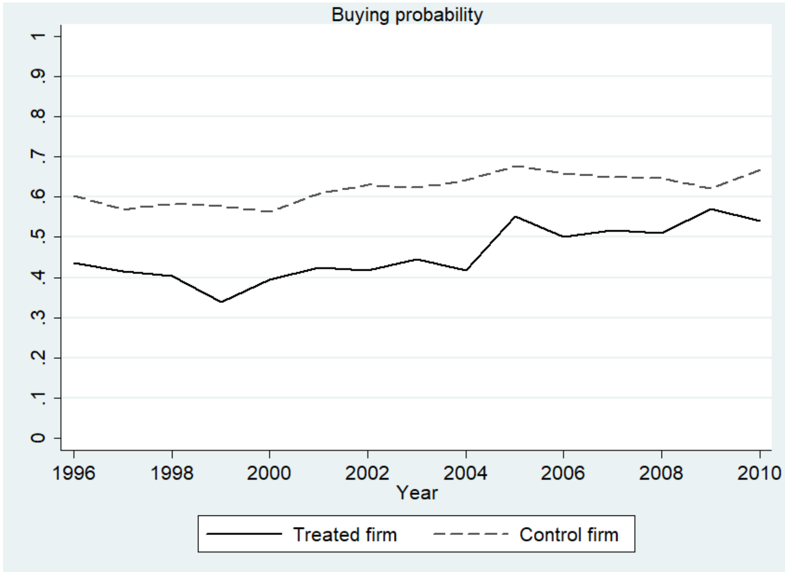
3.7 FIGURES

Figure 5: Evolution of fractions of independent directors on the board and independent boards over 1999 to 2010



Note: This figure presents the evolution of independent boards over 1996 to 2010. *% Independent directors on the board* indicates the average ratio of independent directors and the total number of directors of the board (*Ind dir %*) over time. *% Independent boards* illustrates the percentage of independent boards (whether the board has a majority of independent directors) over the sampling period.

Figure 6: Average Buying probability from 1996 to 2010 for the Treated vs Control firms



Note: This figure presents the evolution of average *Buying probability* for Treated versus Control firms over 1996 to 2010. Treated (control) firms are defined as those that did not (did) comply with the requirement of having a majority of independent directors on the board before 2001.

3.8 APPENDIX 1

3.8.1 Constructing the Dependent Variable

Although PAD database from the USPTO has a number of advantages for tracking patent transactions over a large period of time, it also entails a major challenge in connecting the data to other databases. This is mainly due to the absence of a common firm identifier and the fact that the recorded names of the assignees (buyers) and assignors (sellers) have never been standardized. Since we are interested in the propensity of buying patents, we standardize the names of the assignees, following a similar name standardization procedure to the ones used in Bessen (2009) and Arora et al. (2019). We start by transforming all the names to uppercase and dropping general words (e.g. THE) or phrases (e.g. PAD assignee names may oftentimes include information on potential addresses[47]; Compustat firms may include endings, such as "-CL A", "-OLD", "-NEW") and any punctuation characters. In addition, we standardize common abbreviations, as such different "versions" of INDUSTRIES to IND or TECHNOLOGIES to TECH. Similar to the "stemming" procedure from the NBER data project, we also drop endings indicating legal entities and other common words (e.g., CORP, INC, LTD, IND, etc.), unless the company name is too short (for that we conduct some manual checks). Where possible, we standardize certain company names by their famous abbreviations, for example, we use IBM for various spelling versions of INTERNATIONAL BUSINESS MACHINES CORP (see Arora et al., 2019). Overall, these steps help us decrease the possibilities of spelling inconsistencies.

Another procedure we follow for constructing our dependent variable is the following. To account for our sample firm historical name and ownership structure changes - Compustat variable

[47] For this, we create a directory of countries, states and common cities used in PAD.

conm gets updated for all the available years once a name change is made[48] -, as well as to introduce other spelling variations, we make use of two other databases: Arora et al. (2019) and Monath & McCallum (2015). Arora et al. (2019) data allows us to connect standardized names to parent and subsidiary firms and provides the interval of time corresponding to the specific assignee. Monath & McCallum (2015) helps us identify different "names" for the specific assignee, via tracking all the patents and the corresponding names these patents were filed with. In the end, we are able to create different variations of names for each of our focal firms with information about the time range the name was "active". The goal of all these checks is to ensure that we end up considering the transactions from one firm to another, without including cases of M&As or cases where the firm appears with different names, but is the same entity. After these supplementary checks, we fuzzy match IRRC-Compustat companies with the standardized assignee names from PAD and leave only those transactions, the dates of which are within the range of the previously identified names[49]. If for a given year, the focal firm was matched to an assignee from PAD, we assign a value of 1 to *Buying probability*, and 0 otherwise. Given a) the fact that we are interested in the probability of engaging in buying transactions, rather than for instance, the intensity of doing so (e.g. aggregate number of patents bought from all the transactions for a given year), together with b) the fact that on average, a firm in our sample engages in more than one transaction over the sample period of time, we believe that it is safe to assume that our dependent variable is less subject to concerns of entailing noise due to methodological complexity of constructing it.

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[48] Name changes can be due to different reasons: e.g. ownership changes, corporate decisions.

[49] Importantly, although we do try to minimize type I and type II errors when identifying the firms using PAD, we cannot fully eliminate the possibility that there might be "false" matches.

3.9 APPENDIX 2

Table A 1: Variable descriptions

VARIABLES	**Description** *(all variables are yearly measures at the firm level)*	**Data source**
	Dependent variable	
Buying probability	1 if the firm buys at least one patent in *t* according to PAD, 0 otherwise.	PAD
	Independent variable and moderators	
Ind dir %	Proportion of independent directors out of *Board size* (see below)	IRRC
Treated	1 if the firm was not compliant (did not have a majority of independent directors prior to SOX), 0 otherwise.	IRRC
After_treat	1 if the year is after the year when the firm switched from a non-majority to a majority of board independence, 0 otherwise	IRRC
Research workforce stability	Proportion of the number of firm's inventors that patented in *t-1* or/and *t-2* out of the number of the firm's current inventors patenting in *t*.	Arora et al. (2019); www.patentsview.org
Inventor interactions stability	Average proportion of the firm's inventors' interactions, which are identified at the inventor level, as the ratio between the number of co-inventors with whom each inventor patented in *t-1*or/and *t-2* and those inventors' total number of co-inventors in *t*.	Arora et al. (2019); www.patentsview.org
Inventor team stability	Proportion of the number of teams that patented in *t-1* or/and *t-2* out of the total number of teams that patented in *t*.	Arora et al. (2019); www.patentsview.org
CEO duality	1 if the CEO acts also as the Chairman of the board, 0 otherwise	Execucomp
EINDEX	Entrenchment Index: Number of the corporate governance provisions in place (golden parachute, poison pill, classified board, supermajority vote, limited charter amendment, limited bylaws amendment). See Bebchuk et al. (2009).	IRRC
	Control variables	
Board size	Number of directors on the board	IRRC
Ln(R&D/assets)	Natural logarithm of one plus R&D expenses over lagged total assets	Compustat
Ln(Patents)	Natural logarithm of the number of patents, according to Arora et al. (2019)	Arora et al. (2019)
Ln(Employees)	Natural logarithm of the number of employees (in thousands)	Compustat
Ln(Sale)	Natural logarithm of sales	Compustat
Ln(Firm age)	Natural logarithm of the years since the firm's first inclusion in Compustat	Compustat
Ln(Cash/assets)	Natural logarithm of cash over total assets	Compustat
Leverage	Long-term debt over total assets	Compustat

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